Automatic Recognition of Gait Patterns in Human Motor Disorders using Machine Learning: A Review

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Abstract

Background: Automatic recognition of human movement is an effective strategy to assess abnormal gait patterns. Machine learning approaches are mainly applied due to their ability to work with multidimensional nonlinear features.

Purpose: This review aims to compare several machine learning algorithms employed for gait pattern recognition in motor disorders using discriminant features extracted from gait dynamics. Additionally, this work highlights procedures that improve gait recognition performance.

Methods: We conducted an electronic literature search on Web of Science, IEEE, and Scopus, using "human recognition", "gait patterns'', and "feature selection methods" as relevant keywords.

Results: Literature analysis showed that kernel principal component analysis and genetic algorithms are efficient at reducing dimensional features due to their ability to process nonlinear data and converge to global optimum. Comparative analysis of machine learning performance showed that support vector machines (SVMs) exhibited higher relative accuracy and proper generalization for new instances.

Conclusions: Automatic recognition by combining dimensional data reduction, cross-validation and normalization techniques with SVMs may offer an objective and rapid tool for investigating the subject's clinical status. Future directions comprise the real-time application of these tools to drive powered assistive devices in free-living conditions.

Keywords Lower Limb Motor Disorders; Human Gait Pattern Recognition; Machine Learning Approaches; Dimensional Data Reduction

1 Introduction

Walking is one of the most common human physical activities that can be performed in a variety of conditions and environments [1]. Analysis of human gait patterns can provide significant information related to the physical and neurological functions, and it may contribute to the diagnosis of human motor disorders in pathological conditions [2,3]. For these purposes, the human gait patterns need to be recognized, i.e., categorized according to the situation or clinical status of the analysed locomotor function.

Several studies have argued that automatic recognition of human gait patterns allows us to (i) conduct a quantitative and non-invasive diagnosis of locomotion by comparing the studied locomotor function to a healthy-standard gait [1,4,5], (ii) indicate a subject-specific task for personalized gait training by automatically adjusting assistance in accordance with the users' recognized motor function [6], (iii) plan future treatment according to the user's needs, i.e., according to the user's gait impairment previously recognized through automatic recognition methods [1,4,5], and (iv) quantify and describe the progress of gait treatment by comparing the user's gait patterns at baseline and follow-up moments [1,4,5]. Additionally, these automatic systems for clinical gait analysis constitute an objective technique for massive manipulation of gait data, and they are more quick and cost-effective than the conventional procedures usually used by clinicians [1,7,8].

Various gait disorders have been investigated in the context of pattern recognition to improve initial diagnosis techniques. The injuries that often lead to gait disorders are stroke, spinal cord injury (SCI), Parkinson's disease (PD), cerebral palsy (CP), multiple sclerosis (ME), hip and knee osteoarthritis (OA), and age-related gait impairment. However, the current strategies that have been proposed for the automatic recognition of gait disorders still do not incorporate historical clinical information about the patient in diagnosis analysis [9]. In an attempt to improve the locomotor pattern of neurological injury patients, gait training procedures' have been developed, such as treadmills with or without body weight support, functional electrical stimulation, robotic assistive devices, and the use of virtual scenes that simulate walking in different environments [6,10,11].

To conduct a more comprehensive and reliable recognition of human motor pattern, diverse types of gait dynamics, such as spatiotemporal, kinematic, kinetic and physiological indicators (e.g., electromyographical activity and pulse rate), may be considered since they distinctly describe locomotor function [4,12,13]. Most commonly, the monitoring of these parameters involves expensive but highly accurate systems, such as infrared cameras, optoelectronic systems and force plates [14,15]. As non-ambulatory devices, these sensory systems only operate in controlled environments, [16] and therefore, they have a difficult time analyzing consecutive gait cycles for long-term applications, especially in a free-walking scenario [17,18]. Consequently, current research has focused on the design and application of recognition tools that only use gait dynamics recorded by wearable sensory systems, such as force-contact sensors (e.g., footswitches and foot pressure insoles), accelerometers, gyroscopes, and inertial measurement units (IMUs) [19]. Recent technological advances make these sensors smaller, lighter in weight, easier to don and doff, and cheaper than external sensors. They also have good user compliance and a comparable performance to the external ones [17,20,21]. Furthermore, these measuring devices permit the extension of the recognition process to free-living conditions and foster a more time- and cost-effective categorization of human gait patterns than external devices. Ambulatory recognition with wearable sensors in free-walking environments can also introduce benefits by offering functional robotic-oriented therapies[22–24]. Research groups tend to choose between external and wearable sensory systems at an early stage, so this choice needs to be carefully considered as a function of the research interest of the study.

Considering the potential of automatic recognition and given its contribution to the gait rehabilitation field, we have reviewed recent studies that employed machine learning algorithms in an offline setting to automatically recognize the clinical status of human locomotion. Our reasons for focusing our search on machine learning approaches are three-fold: (i) their generalized ability to the model the complex nonlinear relationships inherent to gait data; (ii) their aptitude to work with multidimensional data; and (iii) their ability to easily incorporate newly data in an attempt to improve prediction performance [7,25,26]. We reviewed studies that exclusively employed gait dynamics recorded from either external (e.g., force plates and motion analysis systems) or wearable (e.g., IMUs and instrumented shoes) sensory systems. We did not include studies that used features encoded as images. In fact, we only analysed studies that extracted features from biomechanical signals that describe the gait. We applied this selection criteria since we propose to disclose a walking recognition procedure that only depends on gait information that may be acquired from wearable sensors to take advantage of this sensory technology. In fact, there are wearable sensory solutions that can monitor the same biomechanical parameters those that are conventionally monitored by optoelectronic systems and force platforms. In contrast, studies that included image-specific features were not investigated given the limitation of the recognition process in the motion analysis laboratory.

This review also provides a comparative analysis of various machine learning methods applied to locomotor patterns classification according to their advantages and drawbacks exhibited in gait analysis. Moreover, we highlight and review pre-processing procedures that are commonly applied before the classification process to improve the performance of gait recognition. In the scope of this review, pre-processing procedures cover methods for dimensional gait data reduction (feature selection methods), methods for cross-validation (CV) and feature normalization. Based on the reviewed information, we identify a standard procedure for human walking recognition using gait dynamics, and address the main search questions raised in this study: (i) What are the most appropriate classification methods to recognize gait patterns using gait dynamics?; and, (ii) What are pre-processing methods that improve the gait pattern recognition? To the best of the authors' knowledge, there are no previous works on the state-of-the-art that address this comparative analysis; this analysis highlight strategies that are capable of performing intelligent, accurate, rapid and cost-effective clinical gait analysis.

The schematic diagram depicted in Fig. 1 highlights the standard procedure for the recognition of human gait patterns using gait dynamics, which involves the following stages: extraction of gait features from gait dynamics; normalization of features; methods to select the most relevant features; classification stage; and, evaluation of the recognition process. This diagram was elaborated in accordance with the surveyed contents, and it consequently states the topics discussed in this review. Section 2 outlines the search strategy conducted in this literature survey and the extracted data. Section 3 describes the mathematical principles and the application of multivariate statistical approaches (used as feature selection methods) in gait recognition. Section 4 highlights and compares the most relevant studies that employed machine learning approaches for offline walking recognition using gait dynamics. Section 5 systematizes strategies to improve the performance of gait pattern recognition namely, feature normalization and cross-validation methods. Conclusions and future directions are noted in Section 6.

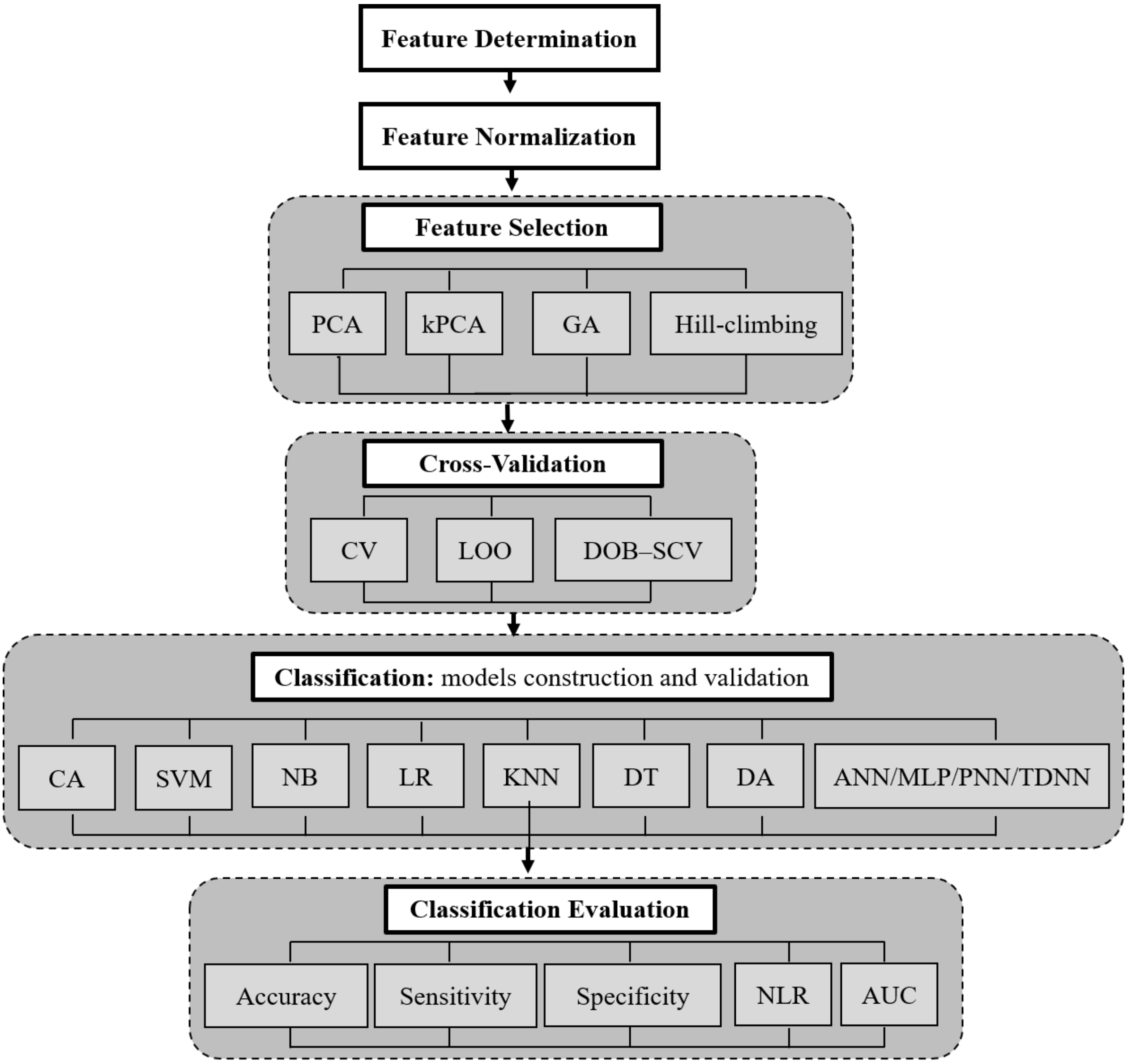

Fig. 1 Schematic diagram of a standard procedure implemented for gait recognition using gait dynamics. The acronyms used in this diagram correspond to the following: linear principal component analysis (PCA); kernel based-PCA (kPCA); genetic algorithm (GA); cross-validation scheme (CV); Leave-One-Out (LOO); distribution optimally balanced stratified CV (DOB–SCV); clustering analysis (CA); support vector machine (SVM); Naïve Bayes (NB); logistic regression (LR); K-nearest neighbors (KNN); decision tree (DT); discriminant analysis (DA); artificial neural networks (ANN); multilayer perceptron (MLP); probabilistic neural network (PNN); time delay neural network (TDNN); negative likelihood ratio (NLR); and area under the curve (AUC).

2 Methods

2.1 Search Strategy

We conducted a comprehensive electronic literature search in Web of Science, IEEE, and Scopus on studies from 2000 onward. In this electronic search, we applied the following keywords: [“human recognition” OR “human classification”] AND [“gait patterns” OR “locomotion”] AND [“impaired gait” OR “pathologic gait”] AND [“offline”] AND [“feature selection methods”]. In addition, wildcard symbols, such as hyphens or inverted commas, were used to consider all possible variations of root words. The search was limited to titles and abstracts.

The papers identified in the initial search were included if they: (i) implemented machine learning approaches to distinguish between pathologic and physiologic locomotion (e.g., healthy/pathological gait and young/elderly subjects) or to recognize pathologic scenarios, such as fall risk and fatigue; (ii) only considered an offline recognition process; (iii) did not involve image-specific features acquired from ambulatory and/or non-ambulatory sensors; (iv) accomplished classification using normalized or non-normalized features extracted from biomechanical data on gait, such as spatiotemporal parameters, kinematics, kinetics and physiological indexes; (v) applied feature selection methods only as a pre-processing technique for the classification stage, (vi) were an original work; and, (vii) were written in English. Works that explored CV methods and other strategies to improve machine learning performance were also included. In addition, we did not impose constraints regarding sample size (number of subjects, number of trials, or number of strides) or the dimension of the features dataset.

2.2 Data Extraction

One researcher (JF) selected the studies and extracted their relevant data. Four researchers analysed and checked the extracted information (CS, JF, JM, and JP). Two different tables were used to extract the data related to the application of feature selection methods (Table 1) and machine learning approaches (Table 2) in the recognition process of gait patterns. For Table 1, we extracted the following information regarding the application of feature selection methods: the study's identification; multivariate statistical approach; goal of dimensional reduction; dataset size and description of involved features; and main results obtained with and without (when available) the feature selection step. The data extracted in Table 2 included the study's identification, goal, number, gender and age of the participants, gait dynamics (description and dataset size, when available), involved feature selection, cross-validation and normalization methods (when available), applied machine learning algorithms, and main results. Additionally, we extracted data concerning the methodologies implemented in the included studies to improve recognition performance (Section 5).

All the information extracted from the selected studies served as the benchmark to broaden and discuss the concepts of the issues in question. A descriptive and comparative analysis was performed since the identified data were insufficient for a meta-analysis.

3 Feature Selection Methods

Recent advances in sensory technologies for data acquisition (e.g., smaller, lighter in weight, and cheaper sensors) have contributed to an enormous increase in the number of empirical signals, which implies *a priori* selection of sufficient empirical quantities for the recognition of patterns [27]. Data reduction techniques based on parameters' selection from gait waveforms (e.g., peak values and magnitudes at specific gait cycle events) are popular due to their simplicity [28]. However, this methodology is often subjective and selects parameters that can highly be correlated [28]. Thus, methodologies for a proper feature selection have been proposed to improve classification performance (e.g., increase accuracy) [7,29,30] by selecting the features that represent the maximal separation between classes [31,32] and providing faster and more cost-effective models [31,33]. These methodologies can be organized into three categories: filter methods (open-loop methods); wrapper methods (closed-loop methods); and, embedded methods (closed-loop methods) [31].

Filter methods work on the dataset without considering the classification algorithm. Subsequently, data analysis involves a heuristic criterion that only depends on inner data properties (e.g., distribution of values and correlation between features) [31,34]. These methods are computationally simple and prompt [31].

On the other hand, the wrapper methods use a heuristic criterion to evaluate the different subsets in accordance with the specific performance of a classifier. Therefore, to select the features, the wrapper methods consider the dataset and the classifier properties, tailoring this approach to a specific classification algorithm [31,34]. These methods are less prone to a local minimum, although they exhibit the risk of over-fitting and are computationally intensive [31].

Embedded methods have the advantage that they include interaction with the classification model; however, at the same time, they are far less computationally expensive than wrapper methods [31].

As illustrated in Fig. 1, the feature selection methods commonly used in walking recognition are PCA and their derived kPCA (both filter methods), GA (wrapper method), and hill-climbing (embedded method) [34,35]. We describe these multivariate statistical approaches in Section 3.1 and disclose their application in recent works in Section 3.2.

3.1 Multivariate Statistical Approaches and Optimization Techniques

Different multivariate statistical approaches that facilitate the interpretation of data based on variance estimation, have been applied in gait data to discriminate relevant information. The aim of the PCA is to find the optimal linear transformation that best represents the data in the least square sense [3], and thus, it does not require the choice of any classifier. It yields a set of orthogonal bases in a new coordinate system and captures the directions of maximum variance in the training data [3,36–38]. The dimensional reduction is performed by keeping the first principal components (PCs), i.e., the values that retain the most variance of the data [3,29].

kPCA is a dimensional reduction technique of nonlinear data that maps the input data into a higher-dimensional feature space through a kernel function (e.g., linear, polynomial and radial basis function (RBF) kernels) [36,39]. Then, PCA method is applied in the feature space to extract the PCs of gait features [36,39]. Recognition studies have demonstrated that polynomial kernel achieves the best performance than linear or RBF kernels [36,40]. In addition, according to Liang and Lee [40], the data projections for even-degree polynomial kernels, particularly 2-degree polynomials, tend to make the clusters linearly separable.

GA is a time-efficient optimization technique that searches the entire data space to find the best solution inspired in the natural selection process in genetics [35,41,42]. First, it randomly creates the populations (data to be processed). Then, in each iteration, GA only keeps the potential candidates that better optimize the cost function defined according to selected classifier (wrapper method) for the next iteration [42,43]. These populations can be processed by three genetic operators: selection, crossover, and mutation [44]. In this sense, the data space is iteratively modified, and GA quickly converges to the global optimum solution [35,42,44]. GA is also able of dealing with multivariable data space and nonlinear input-output interactions [35,42,43,45].

Regarding the hill-climbing algorithm, it is a sequential feature selection algorithm that iteratively searches the features that positively contribute to classification accuracy [46,47]. Hill-climbing uses each feature for an initial classification, and based on the performance of this classification, the features are ranked from highest to lowest [47,48].

3.2 Search Results and Discussion

The feature selection methods noted in Section 3.1 have been used in the dimensional reduction of gait parameters, and they constitute a relevant pre-processing method for gait pattern classification. Table 1 synthesises the purpose, features dataset and recognition results of the seven collected studies that applied feature selection methodologies in offline gait pattern recognition. These studies are the outcome of the search strategy carried out in this literature review, which considered studies published since the year 2000 that exclusively involved feature selection methods as pre-processing in machine learning approaches for dimensional reduction of gait dynamics.

In the seven included studies, four works applied PCA [28,36,38,49], one study investigated kPCA [36], two works implemented hill-climbing strategies [48,50], and the reaming study employed the GA method [44]. Nevertheless, all investigated works integrated distinct features datasets in terms of biomechanical parameters, and sample size. This heterogeneity in the datasets demonstrates that the reviewed multivariate statistical approaches can be applied to discriminate physiological, spatiotemporal, kinematic and kinetic parameters independently of the number of input features. Moreover, such divergence compromises the comparison of the impact obtained by dimensional reduction in offline recognition. Indeed, only one study [36] compared the effects obtained in the classification process by two different feature selection methods namely, PCA and kPCA.

In general, Table 1 shows that the use of feature selection methods improves the accuracy of gait pattern recognition compared to inclusion of the entire dataset. For instance, in one study [49], the accuracy grows from 58% to 95.8% due to proper identification of the relevant features for the classification by applying PCA. Furthermore, Wu *et al.* [36] also showed that identification of the most relevant features by kPCA (17 features against an original dataset of 36 features) augmented the classification accuracy from 85% (no dimensional reduction) to 91% [36]. This behaviour results from the ability of dimensional reduction to create a compact set of uncorrelated features that still characterize the original data without redundancy [47]. Nevertheless, two studies [38,50] reported similar classification performance concerning the accuracy metric, when the entire dataset and a well-reduced features dataset were involved. In these cases, dimensional reduction does not augment recognition performance but it minimizes the complexity of the feature dataset and consequently reduces the computational cost of the recognition process. This finding can particularly be observed in Lai *et al.* [50], where the proposed hill-climbing method selected 32 features from an original dataset formed by 512 features, making the recognition more cost-effective.

Table 1 Studies that employed feature selection methods as a pre-processing strategy in offline walking recognition

Study	Method	Implementation goal	Features		Results
			Dataset size	Description	
Eskofier *et al.* [49]	PCA	Select the spatial and temporal information more relevant in the classification of distinct	84 features per subject (48 in total) from 10 gait cycles	84 spatial and temporal parameters of the segment motion normalized to 101-time steps	Maximum accuracy (95.8%) was reached when using 36 to 39 PCs. The worst distinction between elderly and young

		gait patterns (elderly and young healthy subjects)			gait patterns had an accuracy of 58% using only 10 PCs
Badesa *et al.* [38]	PCA	Study the possibility of reducing the number of features in the evaluation of distinct machine learning approaches (SVM, NB, LR, DA, KNN) in the estimation of physiological states in a robot-assisted training	5 features per subject (7 in total) and per gait cycle, along 5 min of walking	Pulse rate, respiration rate, skin conductance level, skin conductance response and skin temperature	The best classification (91.3% of accuracy) was achieved using the 3 PCs (using feature extraction) and 5 PCs (no feature extraction) in the SVM classifier, meanwhile the worst classification (49.52% of accuracy) was performed by NB with 1st PC
Deluzio *et al.* [28]	PCA	Select the biomechanical features that best characterize the differences between knee OA and control groups	8 features per subject (113 in total) from 5 walking trials	Magnitude of flexion angle, range of motion, phase shift of flexion angle, magnitude of flexion moment during stance, amplitude of flexion moment, phase shift of flexion moment, magnitude of adduction moment during stance, magnitude of adduction moment in first half of stance of the knee	PCA reported that the differences in the gait patterns of patients with knee OA and healthy subjects are characterized by 4 PCs from 8 features. The distinction of the both gait patterns with 4 PCs resulted in an accuracy of 92%
Wu *et al.* [36]	PCA and kPCA	Evaluate if the kPCA's use extracts more significant gait features than PCA, in the classification of young-elderly gait patterns	36 features per subject (48 in total) from 3 walking trials of 10 m	Stride length, stride duration, gait velocity, single support duration, stance duration, swing duration, gait cadence, and hip, knee and ankle angles and angular range of motion during the stance phases, swing phases and three intervals (heel contact to toe contact, toe contact to heel rise, and heel rise to toe-off	The combination of kPCA and SVM achieved best performance (accuracy of 91%) than the combination of PCA with SVM (accuracy of 87%), have been selected 17 and 14 PCs from the 36 gait features, respectively. No implementation of PCA and kPCA resulted in an SVM's performance of 85%
Chan *et al.* [48]	Hill-climbing	Assess if the use of hill-climbing method leads to a smaller subset of features to distinguish the locomotion of younger and older adults by means of MLP, SVM, NB, DT classifiers	14 features per subject (25 in total) from 93 instances recorded along 4 trials	Cadence, symmetry and step regularity in the vertical and anterior- posterior directions, root mean square, integral of power spectral density and stride regularity in the vertical, medio-lateral, and anterior- posterior directions	The application of hill-climbing allowed increasing the accuracy from 82.9% to 84.9% due to dimensional reduction of 14 to 10 gait features
Lai *et al.* [50]	Hill-climbing	Reduce the computational cost of the classification with SVM and extract the most significant features in the distinction between tripping patterns from healthy patterns of adults	512 values per subject (23 in total) from 60 gait cycles performed along 10 min	Minimum toe clearance values	An accuracy of 100% was achieved when 512, 256, 128 64 and 32 features were combined. The worst accuracy of classification was 52.17% when are only used 8 features
Su *et al.* [44]	GA	Verify if the combination of GA with ANN (GANN) is more accurate than the back-propagation algorithm in classification of the gait patterns of patients with ankle arthrodesis and healthy subjects	9 features per subject (20 in total) from 99 pairs of footstrikes	Ground-reaction force parameters normalized to percentage of gait cycle and percentage of body weight	GANN model classified with accuracy up 98.7%, due to selection of the 5 most relevant features from 9 features, while the back-propagation algorithm (without feature selection method) presented recognition rates of 89.7%

According to the reviewed literature [28,29,38,49], we verified that PCA is a widely used technique for dimensional reduction of gait dynamics. However, Wu *et al.* [36] verified that kPCA is able to extract the PCs that contain more relevant information on nonlinear human movement since it works better than PCA in the presence of random noise in gait data [36]. An inconvenience of both PCA and kPCA is choosing how many components (i.e., gait parameters) will be retained in the analysis. As we can see in Table 1, particularly in studies [28,38,49], the selection of correct number of PCs is fundamental to achieving the best possible recognition. Nevertheless, PCA and kPCA are both filter methods, and consequently, they present less complexity compared to other multivariate statistical approaches.

Comparing the hill-climbing and GA procedures, the included studies highlight that the GA method always converges to a global minimum, whereas hill-climbing can converge to a local optimum [35,42,44]. Consequently, to ensure that dimensional reduction increases recognition performance, it is more effective to implement GA rather than hill-climbing. Additionally, GA quantitatively and qualitatively identifies the most relevant gait parameters, without requiring any tuning from the user to indicate the number of features to be extracted. However, GA depends on parameter selection (population size, crossover and mutation probability), and exhibits a higher computational cost than hill-climbing [41].

A particular observation can be formulated by analysing Table 1 and the work proposed in the literature concerning the usual combination of PCA, a long-term studied feature extractor, with the classification model created by SVM [28,36,38,49]. In fact, this combination is very popular within the recognition problems and is independent of the application.

In summary, spite the commonly applied of PCA, based on the reviewed information, we verified that kPCA and GA are appropriate methods for dimensional reduction of gait features for classification due to their ability to process nonlinear data (such as biomechanical gait data) and to converge to a global optimum. Additionally, as GA is a wrapper method, it stands out from kPCA, since it additionally considers the classifier performance during feature selection and feature dependencies. However, selection between GA (a wrapper method) and kPCA (a filter method) should consider both the computational cost and need to integrate the classifier during dimensional reduction (e.g., to avoid subjectivity in specifying of the number of features to be removed), as both methodologies provide reliable results.

4 Walking Recognition

A current clinical challenge is to discriminate a healthy gait pattern from a pathological one and to evaluate the progress of gait disorders during locomotion. For this reason, walking classification methods based on statistical analysis, mathematical transforms, and machine learning approaches have been applied [4]. The statistical analysis approaches have fallen short in meeting the persistent challenges of quantitative and objective analysis, and often, they assume a normal distribution for input data [44,51]. Additionally, mathematical transforms are limited to applications of univariate signals and guideline selection based on wavelets [51].

In contrast, studies [4,50,52] have revealed that machine learning algorithms present a larger ability to both capture patterns and model complex nonlinear relationships in gait data. In addition, these algorithms work appropriately with multidimensional data and easily incorporate newly available data to improve prediction performance [52,53]. The ability to address nonlinear and multidimensional data, such as human gait data, and the capability to properly process newly available data make machine learning approaches suitable methods for human gait pattern recognition. In this sense, this review focuses on machine learning approaches for walking recognition, presenting recent works demonstrating their application in binary and multiclass classifications of gait patterns. The basic principles of machine learning approaches commonly applied in gait classification are described below.

Artificial Neural Networks (ANNs) are a mathematical model inspired by the structure and functional aspects of biological neural systems [42,53]. A standard method of ANNs is a multilayer feedforward neural network that consists of an interconnected set of neurons, where connections between the units only move forward from the input layer to the output layer through hidden layers [7,51,53]. The inputs are mapped to nodes through an input layer, and the outputs are controlled by a transfer function within each node, and it is necessary to adjust the weights of links between nodes to reduce the error function [7,51,53].

Support Vector Machine (SVM) is a supervised leaning classifier that employs kernel methods (e.g., linear, polynomial, and Gaussian RBF) to map nonlinear data (e.g., human gait data, mainly pathological data) to a higher dimensional feature space. Classification is performed in this feature space by finding an optimal separating hyperplane between the analysed classes [26,46,53]. For this optimization problem, parameter C (trade-off between maximum width of margin and minimum classification error) is computed [26,46,54]. Although there are no analytical studies on optimal kernel function, Gaussian RBF is widely suggested as the most convenient option for inter-individual gait classification [55] due to its smoothing behaviour in treating the datasets of interest. The multiclass classification is usually conducted by “one-against-one” and “one-against-all” approaches [56].

Naïve Bayes (NB) assumes that all features are independent of each other according to Bayes’ theorem [38,48]. First, the NB classifier creates a probabilistic model that estimates the probability that an input sample belongs to a certain class. For biomechanical gait data, the probabilistic model is commonly implemented by means of a normal distribution [38,48]. Then, a decision rule is applied to attribute the data to the most likely class [38,48].

Logistic Regression (LR) is a discriminative model for classification that applies maximum likelihood estimation after transforming the output into a logic variable [30,57]. In this way, LR estimates the probability of input features belonging or not belonging to a certain class [30,57].

Discriminant Analysis (DA) aims to find a linear (linear discriminant analysis – LDA) or quadratic (quadratic discriminant analysis - QDA) combination of input features by separating input data into two or more classes, according to a least square sense [38,57,58]. Each input feature has its own assigned weight, which indicates the importance of this feature in discriminating between classes [38].

Clustering Analysis (CA) classifies a data set into homogeneous groups or “clusters”. There are hierarchical and non-hierarchical clustering methods that strive to minimize the variability within clusters and maximize the variability between clusters [59]. In the scope of gait recognition, fuzzy logic clustering is commonly used since it offers an insight into nonlinear relationships among gait variables [60]. It also allows that each input data simultaneously has partial memberships in multiple clusters, and thus a sharp boundary does not exist between clusters [4,60]. Furthermore, K-Nearest Neighbours (KNN) is a non-hierarchical clustering method that defines that the properties of input data based on likely similarity to their neighbours [7,38]. The neighbourhood is defined to include k points, and a distance metric (e.g., Euclidean distance) is used to identify the nearest neighbours of a query point [38]. Thus, k (where $k \geq 1$) nearest training samples are used to classify the new sample with the most common class of k samples.

4.1 Assessment of Recognition Performance

To evaluate the performance of machine learning approaches in gait pattern recognition, three dimensions, namely, accuracy, sensitivity and specificity are commonly used, as shown in Fig. 1. These metrics are obtained based on a confusion matrix [53]. Accuracy, as expressed in equation (1), is the most common and simplest measure to evaluate a classifier, and is defined as the degree of correct predictions of a model by using true positive (TP), false positive (FP), true negative (TN) and false negative (FN) values [33,35].

$$\text{Accuracy (\%)} = \frac{\text{TN} + \text{TP}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \times 100\% \tag{1}$$

Sensitivity, as presented in equation (2), measures the proportion of actual positives that are correctly identified as such.

$$\text{Sensitivity (\%)} = \frac{\text{TP}}{\text{TP} + \text{FN}} \times 100\% \tag{2}$$

Specificity, as showed in equation (3), measures the proportion of negatives that are correctly identified [35]. It is possible to determine the negative likelihood ratio (NLR), a ratio between false and true negatives, through a confusion matrix [30].

$$\text{Specificity(\%)} = \frac{\text{TN}}{\text{TN} + \text{FP}} \times 100\% \tag{3}$$

Another criterion recommended to assess the classification performance, independently of the *a priori* distribution of classes, is AUC [46,48,61]. It presents higher convergence than accuracy and represents the average sensitivity across all possible specificities [30]. AUC is determined through integration by the trapezoid method base on the Receiver Operating Characteristic, a graphic that visualizes the trade-off between the TP rate and FP rate [46,50,53,62].

4.2 Search Results and Discussion

Table 2 lists the most relevant studies since 2000 that employed gait dynamics in machine learning approaches (instead of image-specific features) to discriminate pathological/healthy and young/elderly gait patterns and deficits in the postural balance offline. For each reviewed work, we provide a summary of the study goal, study volunteers, gait dynamics used as features for classification, implemented methods for feature selection, cross-validation and feature normalization, applied machine learning algorithms, and findings of gait pattern recognition. Instances of gait dynamics are ground reaction force (GRF), an indicator of kinetic interaction with the ground, and the minimum foot clearance (MFC), an event that occurs during the mid-swing phase of the gait cycle.

Table 2 Studies that applied machine learning approaches for offline gait pattern recognition

Study	Study's goal	Participants	Gait dynamics	Feature selection	Cross-Validation	Normalization	Classifiers	Results
Alaqtash *et al*. [7]	Automatic classification of pathological gait patterns (CP and ME) from healthy walking	12 healthy subjects (age 27.1±5.9 years), 4 CP (age 29.5±17.5 years) and 4 patients ME (age 50.3±11.5 years)	19 features based on amplitude and temporal parameters of GRFs	M-shaped value and test ANOVA	LOO	Stride-time normalization	KNN and ANN	KNN was more accurate than ANN (accuracy of 85% against 80%) in the classification of 3 gait patterns through GRFs data
Mohammad [45]	Automatic diagnosis of neuro-degenerative diseases (PD, Huntington's disease and ME)	15 subjects with PD (age 66.8 ±2.8 years), 20 patients with Huntington's disease (age 46.65±2.81 years), 13 participants with ME (age 55.61±3.56 years) and 16 healthy subjects (age 39.31±4.62 years)	Temporal parameters: stride, cadence, double support, swing and stance interval (28 samples per subject)	GA	NA	NA	SVM	SVM distinguished the 3 neuro-degenerative diseases of healthy gait patterns with accuracy of 90.65%
Laroche *et al*. [62]	Distinguish the gait patterns of an OA patient from a control subject	20 healthy subjects (age 63.82±6.55 years) and 20 knee OA patients (age 62.23±6.24 years)	12 features extracted from 3D kinematics (1 sample per each subject's stride in a total of 10 gait cycles)	NA	5-fold CV	Body weight-normalization	SVM	SVM distinguished the gait patterns of OA and healthy participants with an accuracy of 88%
Pogorelc *et al*. [5]	Implement an early automatic recognition tool of distinct abnormal gait patterns	5 healthy and 9 pathological elderly subjects (over 65 years): (hemiplegia, PD, pain in the back, pain in the leg)	13 features (angles, spatiotemporal parameters) from shoulders, elbows, hips, knees and ankles (141 samples in total)	NA	10-fold CV	NA	Five-class classification with SVM, DT, KNN, NB and ANN	Accuracy of 97.9%, 90.1%, 100%, 97.2%, 100% for SVM, DT, KNN, NB, and ANN, respectively
Kaczmarczyk *et al*. [59]	Gait pattern classification of post-stroke patients in 3 different foot positions: forefoot, flatfoot and heel	74 post-stroke patients (age 55.6±9.4 years)	11 kinematic variables of knee joint, sagittal and frontal hip joint (1 per subject along 10 m)	NA	NA	Stride-time normalization	ANN (51 input units, one hidden layer of 27 units and one three-level output unit)	ANN correctly classified the post-stroke patterns (accuracy of 100%) when the heel is the first contact
Begg *et al*. [46]	Classification of gait patterns of young and elderly subjects	30 young healthy (age 28.6 ±6.4 years) and 28 elderly participants (age 69.2 ±5.1 years)	Minimum, maximum, median, 1st and 3rd quartile values of MFC (1 sample of each swing phase per subject that walked 20 min)	Hill-climbing	3-fold CV	*z*-score	ANN (three-layer) and SVM (linear, polynomial and RBF kernels)	The best distinction of both gait patterns was achieved with SVM using linear kernel (accuracy of 83.3%), while the ANN showed the worst accuracy (75%)

Begg *et al*. [26]	Classification of gait patterns of young and elderly subjects	12 young healthy (age 28.1±5.6 years) and 12 elderly subjects (age 68.8±4.6 years)	24 spatiotemporal, kinematic and kinetic parameters (1 sample per stride, per subject recorded along 3 trials of 15 m)	Hill-climbing (forward selection algorithm)	6-fold CV	*z*-score	SVM (linear, polynomial and RBF kernels)	SVM with linear, polynomial and RBF kernel achieved the same accuracy (91.7%)
Chan *et al.* [48]	Gait patterns classification of younger and older individuals	13 healthy younger (age 27.7 ±7.3 years) and 12 healthy older adults (age 70.0 ±3.7 years)	14 features: root mean square, integral of power spectral density, cadence, stride and step in the vertical, medio-lateral and anterior- posterior directions (93 samples: 1 per stride and per subject recorded from 4 gait trials)	Pearson Correlation-based method	10-fold CV	NA	MLP, KSart, SVM with polynomial kernel, NB and DT	MLP achieved the best accuracy (80.6%) to discriminate young and elderly gait patterns
Eskofier *et al.* [49]	Gait patterns classification of younger and elderly subjects	24 young healthy (age 25.3 ±2.4 years) and 24 elderly subjects (age 59.9 ±4.5 years)	84 spatial and temporal parameters (1 per subject along 10 gait cycles)	PCA	LOO	Stride-time normalization	SVM with a linear kernel	SVM distinguished the two patterns with an accuracy of 95.8%
Khandoker *et al*. [47]	Automatic recognition of gait patterns related to balance impairments	13 healthy adults (age 67.5±2.1 years) and 10 subjects with history of falls (age 68.2±3.1 years)	MFC data from the first 512 continuous gait cycles of each subject	Hill-climbing	LOO	NA	SVM with linear, polynomial and RBF kernels	Polynomial kernel performed better (accuracy of 100%) than linear (accuracy of 86.95%) and RBF (accuracy of 86.95%) kernels
Lai *et al.* [54]	Propose a gait recognition system to detect fall patterns	13 healthy subjects (age 71.0±2.1 years) and 10 individuals that had suffered tripping fall (age 72.2±2.1 years)	Autoregressive coefficients of 512 MFC values from 60 gait cycles performed along 10 min	Autoregressive model	LOO	NA	SVM with linear, polynomial and RBF kernel functions	The best was achieved with linear and RBF kernel (accuracy of 95.6%), using only 32 MFC samples
Mao *et al.* [63]	Classification of 3 walking patterns: walk stably, intermediary risks of tumble, and high risk of tumble	36 subjects	Maximum, mean and standard deviation values of 4 local motions (motion of head, center of gravity, motion of pelvis, motion of toe) from the first 6 steps	NA	NA	Body height normalization	Multiclass classification with SVM	The three classes were recognized with accuracy of 84.5%
Zhang *et al*. [33]	Recognition of gait patterns during lower extremity muscular fatigue and no-fatigue	17 healthy subjects (age 29±11 years)	Step width, step length, stride duration, heel contact velocity, and stance time (1 sample per subject, per stride along 5 trials)	Kernel function selection method	5-fold CV	Stride-time normalization	SVM with linear, polynomial and RBF kernels	SVM with linear and RBF kernels recognized the fatigued and no-fatigued gait with an accuracy of 96%

Considering the inclusion criteria proposed for this review, we included thirteen studies in this analysis. Five studies (38.46% of studies) focused on the automatic diagnosis of pathologic gait patterns by including a control group formed by healthy subjects with similar demographic features (age and gender) [5,7,45,59,62] Four works (30.76% of studies) recognized the gait patterns of younger and older individuals [26,46,48,49]. Additionally, another study [47] carried out an automatic recognition of gait patterns related to balance impairments, whereas one study [33] investigated the differences between lower extremity muscular fatigue and non-fatigue. The remaining two studies [54,63] proposed a system to detect tripping fall patterns.

By analysing Table 2, we verified that all included studies investigated the performance of SVM for classification purposes, and seven of these studies (53.85%) only implemented this machine learning approach. Five of these studies (38.46%) compare the effects introduced by different SVM kernels [26,33,46,49,54]. Additional machine learning algorithms were explored and compared to SVM namely, ANN (38.46% of studies) [5,7,46,48,59], KNN (15.39% of studies) [5,7], NB (15.39% of studies) [5,48], and DT (15.39% of studies) [5,48].

The majority of the reviewed studies (9 studies, 69.23%) applied feature selection methods [7,26,33,45–49,54], particularly hill-climbing [26,46,47], PCA [49], and GA [45], among other statistical approaches. Additionally, ten studies (76.92%) improved the generalized ability of machine learning approaches by integrating CV methods namely, integrating a conventional CV scheme with different *k*-folds (3-fold [46], 5-fold [33,62], 6-fold [26], and 10-fold [48]), and the LOO method [7,47,49,54]. Normalization techniques were also performed in eight of the thirteen studies (61.54%) through the *z*-score method [26,46] and normalizations as a function of stride duration [7,33,49,59] and participant body weight [62,63].

Diverse pattern recognition methods can be investigated in the scope of human gait, as described in Table 2. From the included studies, we listed some benefits and limitations of the most commonly applied machine learning approaches for gait analysis.

ANN is considered an algorithm with learning capability, adaptability, and ability to address nonlinear data. Nevertheless, this classifier and its feedforward algorithms (MLP, PNN, and TDNN), depend on a large number of parameters for a correct generalization, can get trapped in a local minimum, and can conduct an over-fitting of the training data, harming the generalization of recognition [26,46,50,51].

On the other hand, SVM converges to a global optimum and avoids over-fitting in the training process [31,36]. SVM also has the ability to minimize both structural and empirical risks leading to better generalization of a new classification even, with a limited training data set, and producing stable and reproducible results [26,46,47].

A drawback of both SVM and ANN classifiers lies in their dependence on delicate and computationally expensive hyperparameter tuning of learning parameters (e.g., weights and biases and network size for NN and regularization parameter for SVM) [4,7,64].

CA is very sensitive to variables that are highly correlated, making it necessary to determine and remove these variables [65]. This approach also requires that the number of *a priori* rules and the number of clusters are set *a priori* by the user, implying a subjective judgment [60,64]. However, CA based on fuzzy logic exhibits the benefits of offering insight into nonlinear relationships among gait variables, providing a quantitative comparison, less complexity and fast processing time [4].

Although NB and LR are two probabilistic models, LR does not assume linearity in the relationship between input and output variables and does not assume homoscedasticity; therefore, it does not simplify the computational cost [57].

An advantage of DT and KNN is that the problem of context recognition is divided into smaller sub-problems, which are approached one by one intuitively [66]. Nevertheless, KNN requires the definition of a distance metric, whereas a split criterion must be set in DT.

Due to the deviant behavior of these machine learning approaches, benchmarking can be performed to select the optimal machine learning method for a specific application. For instance, Harper [57] compared DA, DT, ANN and LR methods with distinct datasets and showed that there is not necessarily a single best classification tool; but instead, the best performance of the algorithm will depend on the analyzed features [57]. Other authors have concluded that combining the output of different classifiers can improve classification performance [7]. Additional studies have highlighted that classifier performance depends on many factors, such as the type of input features, dataset size, relevance of involved features, and number of subjects [26,38,50].

Comparative analysis of the findings obtained with machine learning approaches, as outlined in Table 2, led us to observe that in general, SVM is the most accurate classifier for treating gait data, mainly when a Gaussian RBF kernel is involved. The former observation is supported by the following studies: Begg *et al*. [46], who concluded that SVM with linear and RBF kernels performs better than ANN (accuracy of 83.3% versus 75%); and, Badesa *et al*. [38], who noted that SVM with RBF kernel is more appropriate than LR, LDA, QDA, NB or KNN methods. Additionally, Zheng *et al.* [52] investigated the performance of three classifiers (SVM, Random Forest, and KStar) in gait pattern recognition of three neurodegenerative diseases and control subjects. Their results showed that SVM is the most appropriate method to recognize these four classes (control group and three pathologic groups) [52]. Moreover, other studies mentioned that SVM creates a more efficient algorithm than LDA [36,62] and ANNs [26]. Lastly, Novak *et al*. [67] reported that SVM is the most used classification method with a median accuracy rate of 78.76%, whereas the less used classification methods are fuzzy logic and NB with median accuracy rates of 76.05% and 74.70%, respectively [67].

These findings noted that SVM is an accurate classifier in a range of either binary or multiclass recognition tasks concerning healthy and pathological gait and situations of balance instability. The high recognition rates result from SVM's ability to define more complex decision boundaries by applying optimization problems instead of probabilistic ones. Due to this property, SVM classifiers are robust to data bias and data variance, which are commonly observed in human gait data given their inter-subject and inter-step variability, mainly when pathologic gait patterns are considered. Simultaneously, SVM can properly work with the inherent nonlinear character of human gait data and can manage high-dimensional and multidisciplinary data (e.g., spatiotemporal, kinetic, and kinematic parameters) recorded from distinct sensory technologies (either external or wearable sensors). Thus, SVM presents a strong ability to model versatile, complex and nonlinear datasets, such as ones associated with pathological conditions. However, it is worth mentioning that this comparative analysis does not take into consideration the computational cost of the analyzed machine learning approaches. In general, LR has the fastest computational-times, although compared to DT and DA the time difference is likely insignificant in practice. ANN requires significantly more time to train and validate models [57]. Lastly, regarding complexity and the demonstration of reliable performance, SVM is an appropriate tool for offline walking recognition.

5 Approaches to Improving Walking Recognition

In this section, we describe feasible approaches to improving human walking recognition namely, feature normalization and cross-validation methodologies (see scheme in Fig. 1).

CV methods are commonly involved in machine learning approaches as a model assessment technique to evaluate their inter-subject generalization for classifying new instances, mainly when datasets are limited [26,35,36,61] and when they involve pathological information (which exhibits widely variability), as highlighted in Table 2. Moreover, CV methods have the potential to minimize over-fitting of machine learning approaches since the training set is further partitioned into two disjoint subsets: the training subset used to train the learning model; and, the validation subset used to validate the model. In turn, the validation dataset can be used to determine the performance of various candidate models; and thereby select the most general and accurate model [68].

The conventional CV method begins with partitioning a sample into two complementary subsets, the training set and the test set, based on *k*-fold. Thus, the original sample is randomly partitioned into *k* roughly equal size sub-samples, a single sub-sample is used as the validation data for testing the classifier, and the remaining *k*-1 sub-samples are used as training data. Consequently, the CV process is repeated *k* times until every gait trial of the dataset is included in the testing dataset. Lastly, the average of the *k* results is calculated to obtain a single performance estimation [4,7,35,61,69]. The advantage of this method is that it matters less how the data gets divided. In the literature, there is no a stipulated number for *k*-fold, although many studies have implemented a 10-fold [5,48,70] or 5-fold CV scheme [33,62].

However, recent studies preferred LOO [7,47,49,54], a robust CV procedure, since it does not randomly partition the data. Instead, data in each fold belong to a particular participant [7,38,50,53,66], i.e., LOO partitions data using the *k*-fold approach where *k* is equal to the total number of observations in the data. In addition, López *et al.* [61] considered that CV is not appropriate in situations of unbalanced and covariate data since it may introduce a different data distribution between the training and test partitions by equally partitioning the number of samples of each class on each partition [61]. According to López *et al.* [61], the distribution optimally balanced stratified cross-validation (DOB-SCV) is a proper methodology that avoids both unbalanced and covariate data issues [61]. DOB-SCV picks a random unassigned example and then finds its *k*-1 nearest unassigned neighbors of the same class. Posteriorly, *k* closest neighbors are placed in different folds (with *k* being the number of total partitions) to maintain the data distribution between the training and validation partitions [61]. The process is repeated until there are no more instances [61]. Fig. 2 illustrates a graphical representation of these different CV methods to elucidate the principles of each method.

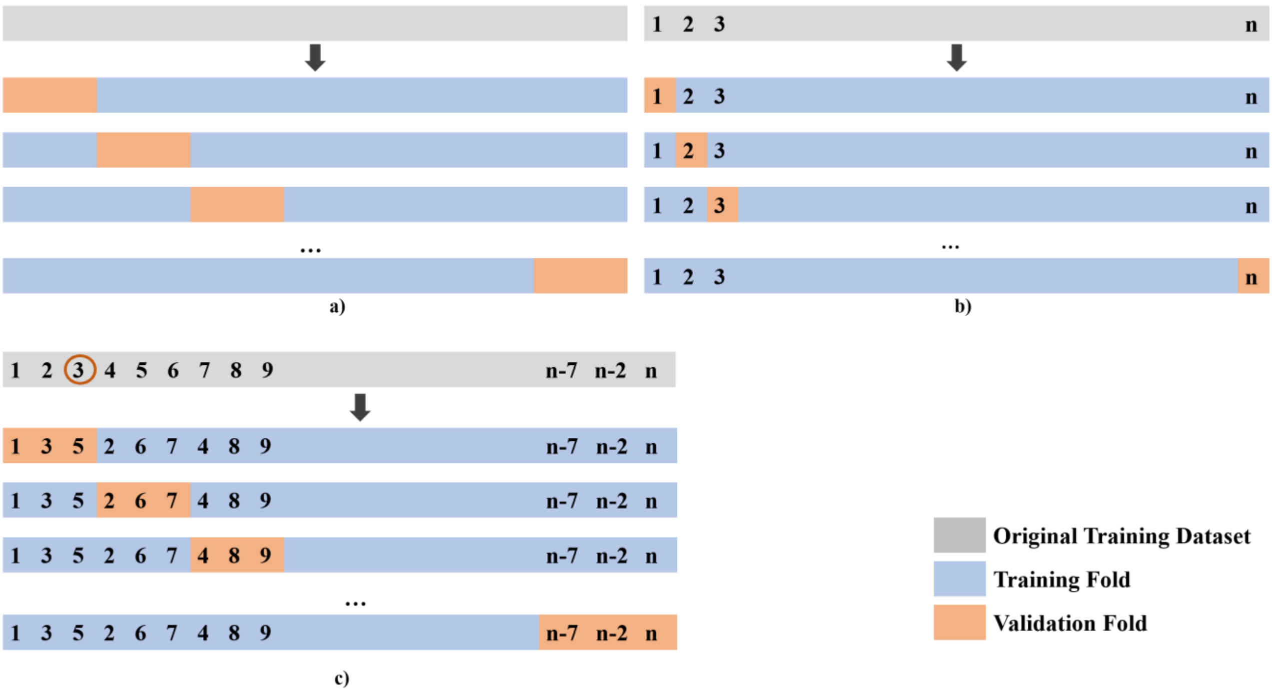

Fig. 2 Graphical representation of CV methods: a) conventional *k*-fold CV method, where the original training dataset was partitioned in *k* partitions; b) LOO CV method, which uses each sample (identified by 1, 2, 3, … n) as a validation fold; c) DOB-SCV method, where for instance, sample 3 (randomly selected) and its neighbors 2 and 4 where assigned to different folds.

Another approach commonly used to make the classifiers more robust and improve their accuracy is the prior standardization of features [26,36,71], as outlined in Table 2. For this purpose, the *z*-score is often implemented on the original feature as set by equation (4), where x is the feature, μ is the mean and σ is the standard deviation [26,36,46]. Thus, each feature has a mean of zero and a variance of one [3,33].

$$\frac{x-\mu}{\sigma} \tag{4}$$

Time normalization is also a common standardization method that expresses each feature as a function of the stride (gait cycle) in percentages rather than in time [4,7,33,49,59]. A similar strategy has also been applied to kinematic features through participants body weight instead of the stride duration [62,63].

In addition, there are specific methodologies for each machine learning approach. To avoid ANN over-fitting, techniques other than CV methods, such as regularization, pruning or Bayesian model comparison, can be used to indicate the tipping point when further training no longer results in a better performance [53]. Additionally, Begg *et al.* [46] proposed a scaled conjugate gradient algorithm to adjust the weights of the ANNs since it allows training of the relationship between gait features and the respective gait class [46]. Su *et al.* [44] demonstrated that the combination of a GA algorithm with ANN is more accurate than the implementation of

ANN based on a back-projection algorithm. The performance of SVM is extremely dependent on tuning of the regularization parameter (parameters C and σ), and therefore, a grid-search is often implemented to find the best values of C and σ, minimizing the misclassification error [46,47]. Hsu *et al.* [72] recommend that the grid-search is combined with a CV method to ensure that the values are most appropriate for the input dataset [72].

The described approaches represent some strategies able to improve the classifier performance during gait pattern recognition, aside from the implementation of feature selection methods. Indeed, we verify that the implementation of these approaches, or other ones with the same purpose, contributes significantly to the reliability of the developed recognition tool.

6 Conclusions

This literature review covers the state-of-the-art on machine learning approaches, and their respective pre-processing methodologies, for human pattern gait recognition using gait dynamics. The reviewed methods may vary based on supervised and unsupervised learning; linearity and nonlinearity models; the possibility of leading to over-fitting or not; division of classification in training and test phases or not; and on the necessity of defining split criteria or not.

Human gait pattern recognition is a powerful automatic tool that may provide an objective analysis of abnormal gait patterns, by manipulating nonlinear and massive multidimensional datasets. Recent studies have evidenced that wearable sensory systems provide these datasets given their potential for long-term and free-setting applications, and a time- and cost-effectiveness.

From this literature analysis, we verify that proper and reliable gait pattern recognition should involve several phases. The first phase is feature extraction to characterize the gait pattern (e.g., healthy/pathological, or old/young). Second, methods of feature normalization may be applied to achieve a more robust classification. Then, feature selection methods are implemented to select the most significant features to distinguish the classes based on dependence of classifier performance on the number and type of features. kPCA and GA are promising methods for dimensional reduction of gait parameters due to their ability to work with nonlinear data and converge on a global optimum. The next stage before the classification algorithm is to form the training and testing datasets through CV procedures, mainly LOO. CV methods also prevent over-fitting and generalize the classifier performance. The implementation of these three methodologies provides the answer to the second search question raised in this review since these are reliable tools that improve the performance of walking recognition. Out of the three existing classification methods, machine learning approaches are the most successful ones when applied in gait pattern recognition due to their ability to work well with multidimensional nonlinear features. Nevertheless, SVM stood out as an accurate tool that converges to a global minimum, does not lead to over-fitting, and minimizes both structural and empirical risk, leading to better generalization for new data classification. The main limitation of SVM is its dependence on a proper choice of input parameters, which can be solved by combining a grid-search with the CV method. In response to the first search question proposed in this review, we have concluded that SVM has the potential to become a powerful tool for human walking recognition in clinical applications.

In summary, an automatic recognition of gait disorders through machine learning algorithms is likely to offer an objective and prompt assessment of the subject's clinical status and hence, provides a potentially realistic diagnosis. However, the classification of data is not necessarily equivalent to diagnosis, as there should be sufficient clinical evidence supporting such an argument in specific cases/conditions. This fact agrees with a major drawback of the described techniques which is that they do not consider the subject's clinical history.

Future directions involve the successful application of machine learning approaches in real-time monitoring of human gait during daily living activities. This scenario will provide a more reliable, prompt, and cost-effective diagnosis of locomotion. Moreover, real-time recognition and assessment of gait patterns can drive powered assistive devices and promptly plan task-oriented therapy in pathological conditions.

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The authors declare that they have no competing or conflict of interests.

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