Classification of Neurological Gait Disorders Using Multi-task Feature Learning

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***Abstract*—As our population ages, neurological impairments and degeneration of the musculoskeletal system yield gait abnormalities, which can significantly reduce quality of life. Gait rehabilitative therapy has been widely adopted to help these patients retrain central nervous system physiology to maximize community participation and independence. To further improve the rehabilitative therapy provided to the patients, more objective methods need to be used and rely less on the subjective judgment of the therapist and patient. In this paper, an algorithmic framework is proposed to provide classification of gait disorders caused by two common neurological diseases, stroke and Parkinson's Disease (PD), from ground contact force (GCF) data. An advanced machine learning method, multi-task feature learning (MTFL), is used to jointly train classification models of subject's gait in three classes, post-stroke, PD and healthy gait. Gait features that can capture gait patterns related to mobility, balance, strength and gait phases are used as features for the classification. Out of all the features used, the MTFL models capture the more important ones per disease and help provide better objective assessment and therapy progress tracking. To evaluate the proposed methodology we use data from a human participant study, including five PD patients, three post-stroke patients, and three healthy subjects. Despite the diversity of abnormalities caused from each disease, the evaluation shows that the proposed approach can successfully distinguish post-stroke and PD gait from healthy gait and post-stroke from PD gait, with Area Under the Curve (AUC) score of at least 0.96. Moreover, the methodology helps in important gait feature selection which may help in better understanding the key characteristics that distinguish abnormal gaits and help in the target design of treatment.**

I. Introduction

Aging is an unprecedented, pervasive, profound and enduring process for humanity, and currently a global phenomenon [1]. One major challenge associated with aging is the degenerative conditions of the neuromusculoskeletal system (e.g. osteoporosis, arthritis, Alzheimer's disease [2], stroke [3], and Parkinson's disease [4]). Any dysfunction of the central nervous system, spinal cord, peripheral nerves or muscles can result in an abnormal gait [5]. At the age of 60, 85% of people have a normal gait, but at the age of 85 or older this proportion drops to 18% [6]. As a result, an increasing number of people suffer from walking difficulties, and the demand for gait rehabilitative therapy has been increasing rapidly.

In the current practice, gait rehabilitative therapy is provided by therapists who manually stimulate patients' reflexes and rotate their lower limbs to retrain their central nervous systems with the correct gait patterns. This approach is not only physically demanding for both patients and therapists, but also expensive and time-consuming. Moreover, in the clinic, assessment of gait abnormalities is based on timed tests, visual observations by therapists, retrospective qualitative evaluations of video tapes, and specific physical tests, e.g., strength, range of motion, balance, gait speed, and endurance. As a result, most times gait assessment is based on the subjective judgment of the therapist. More objective methods are desired to quantify the gait assessment and progress evaluation of the rehabilitative training, reducing the chances of biased assessment by the therapists and providing better, targeted treatment to the patients.

Significant research efforts have been made to provide more objective gait assessment. Different sensory devices have been employed for gait analysis and impairment diagnosis. For instance, encoders, inertial sensors, camera-based motion capture systems have been employed for kinematic analysis of human motion [7], [8]; force sensors [9], [10] and electromyography (EMG) sensors [11] have been widely used to study the ground contact forces (GCFs) and muscle activities during walking; electroencephalography (EEG) sensors have been employed to analyze brain signals [12], [13] and better understand neurological mechanisms of walking. Advanced signal processing and data analytic methods have been applied on data recorded from such sensor platforms [14], [15], [16], [17], [18], [19]. These sensor technologies along with smart classification tools could be used to detect or prognose various disorders that are related to everyone's gait. Additionally, disease monitoring and therapy progress tracking can be easily achieved with the described sensor technologies, since access to gait data is going to be cheap and pervasive, highly reflective of daily life, which is hard to get in the clinic under constrained and highly unnatural circumstances [6].

To better quantify abnormal gait, important sensing features need to be identified to characterize a gait disorder. Towards this goal, extensive research efforts have been reported to use machine learning algorithms for gait classification and clustering, to identify such parameters and automate gait disorder diagnosis. For example, post-stroke patients usually experience a very diverse set of gait abnormalities, most common of which is the hemiplegic gait [5]. For this reason, researchers have applied cluster analysis to identify subgroups of patients with similar sensing features who experience similar gait abnormalities [17], [18], [19]. Likewise, other research efforts focus on classifying abnormal gaits between healthy subjects and Parkinson's disease (PD) patients [15], [16], [20]. Through feature selection methods, important gait parameters can be identified that distinguish abnormalities from normal gait, thus helping the target design of treatment and the evaluation of therapy progress [21]. Additionally, such tools can improve the valuable clinical management of the patients, ease communication between clinicians [21] and optimize subject selection for human participant studies [22]. Consequently, they reduce the cost of physical therapy and improve the quality of life for patients. Especially, patients living in remote areas can benefit from an enhanced tele-medicine system with these quantitative tools, without necessitating complex apparatus [21].

Due to the lack of such a complete diagnostic tool for gait disorder diagnosis, we propose an integrative framework in this paper to automatically classify gait disorders from two common neurological diseases, stroke and PD, and distinguish agnormal gait caused by these two diseases from halthy gait. To the best of our knowledge, there is no such quantitative gait diagnostic system for these two diseases. Classifying gait into groups caused by these two major neurological diseases can lead the way to providing diagnostic tools for specific gait disorders caused by these two neurological diseases, which is much needed for assisting objective gait assessment in the clinic and rehabilitation therapy centers. Our integrative framework includes a pair of smart shoes as the sensory device to capture the GCF data and a pipeline of data analytic algorithms for feature extraction from gait patterns and classification. Gait features are extracted from the sensory data and are used to describe gait, including features for mobility, balance, strength and gait phases.

Because there is relatedness in the gait disorders resulted from the two neurological diseases, multi-task machine learning strategies can be more feasible to identify similarities and differences of gait patterns than classic multi-class classification algorithms given multi-class classification methods focus on modeling only the exclusive (or discriminative) features of the different gait classes. An advanced multi-task learning algorithm has been developed and used to jointly create three classifiers, respectively, for distinguishing stroke-induced abnormal gait from healthy gait, PD-induced abnormal gait from healthy gait, and PD-induced gait from stroke-induced gait. The advantage of our multi-task learning method is that it can identify features useful for all three classification tasks as well as those predictive of a specific abnormality.

The remainder of the paper is organized as follows. Section II reviews the related works in gait quantification and analysis. Section III briefly presents the sensory device that we developed to capture the GCF data and section IV discusses the gait parameters we extracted based on the data. In Section V, we introduce and examine the multi-task learning approach and use it to classify gait based on the extracted GCF features. Evaluation results are given based on the data from a human participant study and findings are summarized in Section VI. We conclude the paper and discuss future work in Section VII.

II. Related Works

Extensive research efforts have been made towards quantitative gait analysis. In this section, we first discuss the literature studies on improving gait quantification methods for objective gait parameters extraction. We then present in Section II-B a summary of on machine learning methods for improving gait analysis, which includes gait patterns classification and cluster analysis for finding subgroups of patients who suffer from the same neurological disease and experience similar gait abnormalities.

A. *Gait quantification*

Gait quantification is an important aspect of objective gait assessment and analysis. It relates to the methods used for objectively measuring gait parameters, which can be used to estimate the severity of someone's gait abnormalities and compare it with other individuals. In this subsection we discuss gait quantification with respect to hemiplegic and Parkinsonian gait, which are the two most popular gait disorders caused by stroke and PD respectively [5].

Among many gait parameters, symmetry is an important gait characteristic and is defined as a perfect agreement between the actions of the lower limbs [23]. It can provide insight about the control of walking which may be unique from more conventional measures such as velocity, and may have a role in guiding the clinician's treatment decisions [24]. Popular parameters used to calculate symmetry include mobility parameters, like single support ratio and spatiotemporal parameters like step length [24], [25]. Symmetry indexes (SI) have also been developed as well, to determine symmetries in GCF patterns [23], [14].

Balance or walking stability is another important parameter that needs to be quantified, that can also be used to predict falls. In [26] multiple balance and stability measures are proposed using IMU sensors, including RMS acceleration and jerk (time series of first derivative of acceleration), to represent the rate of change in acceleration. Jerk scores should be smaller for healthy people. Other measures reported are sway, a measure on how much a person leans his/her body, step and stride regularity and variability [26]. Mobility and gait phases are also important gait parameters used to quantify gait. Mobility parameters include general movement characteristics like cadence, step length, single and double support ratio and periodicity, which is calculated from acceleration autocorrelation [27], [24]. Gait phases refer to the various states within one walking cycle, and there are typically eight gait phases for a healthy subject [28], [29].

Gait quantification can be used to extract gait features which can be used to perform gait pattern classification. In this paper we use standard gait parameters for mobility, balance and strength quantification, that can be easily calculated from GCF data. In addition, new gait phase parameters are introduced based on our previous work [28]. In the next subsection we discuss related works on gait pattern classification and cluster analysis. In our previous work a wireless human motion monitoring system was designed [30] to supplement gait analysis. A real-time data-driven gait phase detection algorithm was developed to capture the gait phases using GCF data [28]. The proposed system can objectively quantify the underlying gait phases without input from a medical professional. These two works contribute with some of the gait parameters used in this paper.

B. Gait pattern classification

Extensive research efforts have been reported to perform cluster analysis of post-stroke gait patterns, so appropriate development of targeted treatment can be done. In [17] non-hierarchical cluster analysis was used to categorize four subgroups based on the temporal distance and sagittal plane joint kinematics. Differences in muscle strength and muscle activation patterns during walking were identified among groups, according to the recorded EMG data. Similarly, hierarchical cluster analysis of gait patterns of post-stroke patients with equinus deformity of the foot was conducted in [18]. Three groups of patients were identified, with homogeneous levels of dysfunction, named: the fast walking group, the slow walking group and the combined slow walking and knee hyperextension group. In [22], k-means clustering was used to group gait patterns in order to optimize participant selection in a biofeedback pedaling treatment.

Classification of post-stroke gait patterns is another example of using machine learning methods in gait analysis. In [19] a large set of gait differences was observed between hemiparetic and healthy control subjects at matched speeds, using kinematic and insole pressure data. In [27] accelerometry data were used to extract gait parameters from a group of post-stroke subjects and a control group of healthy subjects. It was reported that accelerometry gait parameters can discriminate stroke patients' gait from the control groups' gait. Artificial neural networks (ANN) were used in [31] to classify post-stroke patient's gait into three categories based on the type of foot position on the ground at first contact: *forefoot, flatfoot* and *heel*. The work in [21] intended to develop a new gait classification method for adult patients with chronic hemiparesis, and to validate its discriminatory capacity. They classified gait in three groups with two subgroups each, that were defined from clinical knowledge. This classification enables patients to be grouped on the basis of key abnormalities observed whilst walking and has the advantage of being able to be used in clinical routines without necessitating complex apparatus.

Given the remarkable diversity of gait deviations observed in post-stroke patients, most of the research efforts focus on studying a limited set of gait abnormalities and thus related gait parameters. For example, in [18] only patients with reduced knee flexion participated in the study and in [31] focus was only given to the subject's foot position on the ground. Extending those works to support classification of a broader set of gait disorders is very challenging. The currently used gait parameters need to support the classification of new disorders and provide statistical evidence in validating the differences between groups. Close cooperation with physical therapists and medical professionals is needed to design and select appropriate gait parameters.

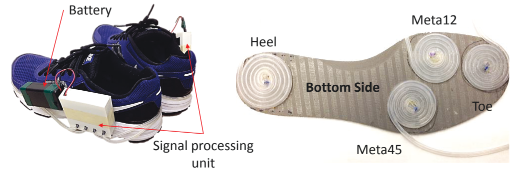


Fig. 1: An overview of the smart shoe design. A signal processing unit includes barometric sensors, microcontroller, and Bluetooth chip

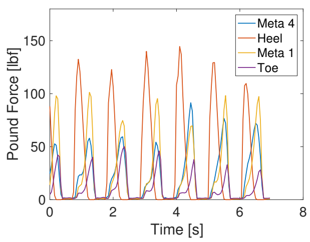
In this paper, we perform classification of gait patterns in three classes, healthy, Parkinson's and post-stroke. To the best of our knowledge, there is no research work on classification of gait patterns between these three classes. We employ a comprehensive set of gait parameters from four different categories. We use standard gait parameters for mobility, balance and strength quantification. Additionally, new gait phase parameters are introduced based on our previous work [28]. These parameters are sent as input features to a classifier. An advanced classification method, MTFL, is used to distinguish between the three gait classes. Before we discuss the details of our algorithmic framework, we present our smart shoe design for GCF data collection.

III. Smart Shoe Design and Ground Contact Force (GCF) Data

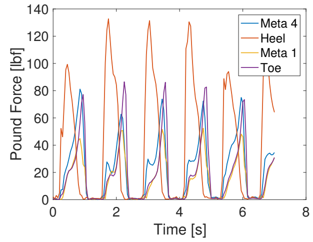
In order to better analyze patients' gaits during walking, we have developed a pair of smart shoes to measure the GCFs on both feet [30], [32]. Fig. 1 gives an overview of the shoe design. Four barometric sensors are employed to measure the GCFs on the toe, the first and second metatarsophalangeal (MTP) joint (Meta12), the fourth and fifth metatarsophalangeal joint (Meta45), and the heel. Silicone tubes are wound into air bladders to connect barometric sensors with measurement ranging from 0 to 250 mbar. Each sensor can measure weight up to 200 lbs with a resolution of 0.2 lbs.

The pressure sensor outputs are read by a microcontroller through analog input channels and the sensor signals are sent out using a Bluetooth module. The Bluetooth module can smoothly and reliably transmit signals within 200 feet to the receiver, which is enough for normal clinical and daily use. A 9-volt alkaline battery is used to power the smart shoes, and it can work consecutively for 90 minutes. The sampling rate of the smart shoes can go up to 100 Hz with the Bluetooth module. In this paper the sampling rate used is 20Hz. Representative raw data from each of the three classification classes can be seen in Fig. 2. **To Wenlong: It**

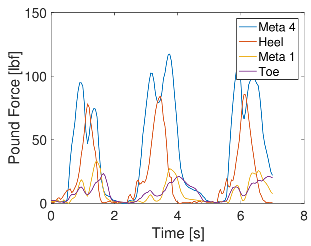
would be great if you could help to briefly describe the differences in raw data



(a) GCF data from a healthy subject



(b) GCF data from a PD subject



(c) GCF data from a post-stroke patient

Fig. 2: Representative raw GCF data from the three classes of gaits, i.e. healthy subjects, PD and Post-Stroke patients

Category	Gait Features	Laterality
Gait Phases	Exp. Num. of Gait Phases	Unilateral
	Symmetry of Gait Phases	Unilateral
	Num. of Swing Phases	Unilateral
	Symmetry of Swing Phases	Unilateral
Mobility	Cadence (steps/min)	Bilateral
	Double Support Ratio	Bilateral
	Single Support Ratio	Bilateral
	Stance Phase Ratio	Unilateral
Balance	Max. Force Difference between Meta12 and 45	Unilateral
	Min. Force Difference between Meta12 and 45	Unilateral
Strength	Max. Force of Heel Strike	Unilateral
	Max. Force of Toe Off	Unilateral

TABLE I: Proposed twelve gait features in four categories

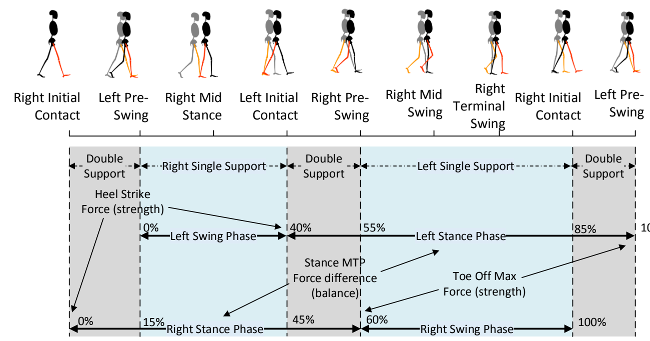


Fig. 3: An overview of a gait cycle and the gait features

IV. Gait Features Extraction

Describing specific human gait disorders accurately is often a difficult task [6]. Consequently, it is challenging to devise gait features [1] that can be used to classify gait patterns. Furthermore, the GCF data collected from the smart shoes can be noisy, as any wearable sensor data, due to imperfect sensor dynamics and complexity of human gait. In this section we present a set of gait features that are used to detect the gait abnormalities by capturing the key gait characteristics of post-stroke and PD patients.

In Table I, fourteen gait features are proposed based on the GCF sensor signals collected from the smart shoes. These fourteen featues are organized into four categories: mobility, balance, strength and gait phases. Their details will be discussed in the following subsections. Among these features, double support ratio, single support ratio and cadence are comprehensive features, which require bilateral information. All the other eleven features are unilateral, as they can be calculated for each side separately [33].

A. Gait Cycles

We first give an overview of what a gait cycle is, since all the gait features are extracted once for each gait cycle in a walking trial. Gait cycle is the time interval between the same repetitive events of walking. The defined cycle can start at any moment, but generally begins when one foot contacts the ground. If it starts with the right foot contacting the ground, the cycle ends when the right foot makes contact again. Fig. 3 gives an overview of such a gait cycle, where two gait cycles are shown at the lower two horizontal solid lines. The gait cycle can be broadly divided into two phases: stance phase and swing phase [5]. These two phases can then be further divided into sub-phases within the gait cycle, as shown at the top part of Fig 3. In general, the stance phase takes around 60% of the gait cycle [5] and can be divided into double support and single support. In double support, both feet are in contact with the ground, while in single support only one foot is in contact with the ground. Double and single support ratio refer to the portion of time whithin a gait cycle someone spends in double or single support respectively. The swing phase is described when the limb is not weight bearing and represents around 40% of a single gait cycle [5]. These percentages can change with the walking speed, as with higher speeds double support ratio in the gait cycle tends to be reduced. In fig. 3 the lower depicted cycle starts with right foot initial contact, which leads to the stance phase, while the other starts with left pre-swing phase which leads to swing phase. Indicative percentages are shown to indicate the different phases within the cycle.

In Fig. 3 different categories of gait features are shown for different categories, like mobility, balance, strength and gait phases. In the subsection IV-B we discuss how gait phases are extracted and what gait phase related features are used in this work for gait disorder diagnosis. In subsection IV-D and IV-E we discuss other features we use related to mobility, balance and strength.

[1] In the remainder of this paper we refer to gait parameters, the term used in most of the literature studies, as gait features to avoid confusion with the model parameters used in the multi-task learning methods to be presented in Section V.

B. Gait Phase Detection

Gait phase refers to various states within one walking cycle, and there are typically eight gait phases for a healthy subject (as shown at the top of Fig. 3): initial contact, loading response (or pre-swing), mid-stance, terminal stance (or initial contact), pre-swing, initial swing (not shown in Fig. 3), mid-swing, and terminal swing [30], [32]. Pathological gait can be unpredictable and complex, thus some gait phases might be missing and the time allocation of gait phases might also be different from a normal gait. This abnormal gait phase allocation provides a powerful tool for abnormal gait detection.

In the current work we use our previous work on gait phase detection which utilizes parallel particle filters to estimate a posterior distribution of gait phases from the observed GCF data [28]. Our non-parametric Bayesian approach estimates the unknown number of gait phases that can be best described from the GCF data. We chose Dirichlet for the gait phase prior probabilities and Gaussian and inverse Wishart for the parameters of the infinite Gaussian mixture model (IGMM) that represents the mixture of gait phases. The model is estimated by sampling and the popular chinese restaurant process (CRP) is used for this purpose. In the rest of this subsection we describe the process of identifying swing and stance phases from the extracted gait phases.

Although it is straightforward to find healthy gait's swing phase (Fig. 3), the swing phase detection in pathological gait can be challenging. There are several reasons why this can be the case. First of all, the way smart shoes are worn can affect the raw GCF sensor signals. Tight shoe laces will change the raw values recorded by the barometric sensor, leading to different absolute values even for the same person in different sessions. Additionally, the stochastic nature of the sampling, which is used to estimate the distribution of gait phases [28], can sometimes introduce new gait phases, which are not eventually represented in the GCF data. Finally, pathological gait can be so complex that sometimes new gait phases are explored from the particle filter algorithm. Notice that the gait phase detection algorithm is not supervised, so the detected gait phases do not have any labels. Apart from that, various conditions of neural or muscular impairments, like foot-drop, can cause fore-foot dragging on the ground [5]. In such cases new gait phases are likely to be discovered which should be identified as swing phases, as gait cycles will be otherwise affected and thus many more parameters.

For all these reasons it is critical to identify which of the discovered gait phases are corresponding to swing phase. We need this information as many gait features to be discussed later, including double support ratio and single support ratio, need to be evaluated in only swing or stance phases. For gait phases related to foot-drop, where the affected foot is not completely in the air, we still consider them as swing phases, as we don't want to have the other gait features affected.

As we described earlier, healthy gait swing phase ratio (portion of time spent on swing phase) is typically around 40% [5] of the gait cycle, as shown in Fig. 3. This may change depending on the speed of walking. Pathological gait can have smaller swing phase ratio, as the patient is walking slowly. Also, in the swing phase, GCF measurements will take very small positive values (or zero), as pressure from the body is not present in that limb. Using these two properties we identify the swing phases from all discovered gait phases according to the following steps:

We first calculate the average euclidean distance for all the observations in each gait phase from 0, by taking its 2-norm. We then sort the gait phases in increasing order based on their norms. We create a new swing phase, and add the observations in the sorted gait phase list one by one until the total number of observations represented from the new swing phase is more than 10% of all the observations. The 10% threshold is empirically chosen and gives the desired swing phase ratio in our dataset. The number of swing phases that were merged to one is kept as it is used as a gait phase feature. All of the gait phase features extracted from the gait phases are described in the following subsection.

C. Gait Phase Features

The gait phase features are calculated from the gait phases that are extracted by our gait phase detection algorithm (see Section IV-B and for more details, please refer to [28]). The expected number of gait phases can be calculated from the particles and their weights returned from the particle filter algorithm as $\bar{K} = \sum_{i=1}^{N} w_i K_i$, where K_i is the number of gait phases detected from particle i and w_i is its weight. $\bar{K}$ is a measure of the complexity of the human gait. Compared with the eight standard gait phases of a healthy subject, pathological gait is unpredictable and it may have a different number of gait phases. For example, post-stroke patients with affected neurological system may experience foot-drop. This usually increases the stance phase with circumduction to allow toe clearance [5], which can lead to toe dragging on the ground, leading to the gait phase detection algorithm detecting multiple swing phases. The number of swing phases is another gait parameter and can be found as described in the previous section.

The symmetry of gait phases (swing phases) is used as a measure to quantify how evenly the proportion of time spent in each gait phase is in a gait cycle (swing). We chose to include this new type of symmetry measure as it can be easily applied on the gait phases that were extracted from our Dirichlet process mixture model [28], given the fact that number of gait phases is not known *a-priori* for each subject. This single gait parameter can estimate the symmetry for any number of gait phases detected. It is based on the cosine similarity, as described in the following formula:

$$cos(\theta) = \frac{\mathbf{g} \cdot \mathbf{u}^T}{||\mathbf{g}|| \cdot ||\mathbf{u}||} \quad (1)$$

where θ is the angle between $\mathbf{g}$ and $\mathbf{u}$, with $\mathbf{g}, \mathbf{u} \in \mathbb{N}^K$ and K is the number of gait phases (swing phases) found. $\mathbf{g}$ is a vector of size K, where each element in $\mathbf{g}$ counts the number of observations belonging each gait phase (swing phase) within a gait cycle and $\mathbf{u}$ is a vector of size K with all its elements equal to 1. If the number of observations belonging in each gait phase are not evenly distributed and thus there are gait phases with very few observations, the angle between vector $\mathbf{g}$ and $\mathbf{u}$ will be higher resulting in lower symmetry. On the other hand, if the number of observations belonging in one gait phase are always more than normal it would lower the symmetry. This could indicate some abnormality, which can be easily captured by this parameter.

D. Mobility Features

We select four features in the mobility category, double and single support ratios and stance phase ratio. Cadence is measured in steps per minute and it is calculated by taking the total number of gait cycles in one trial devided by the length of the trial in minutes, it is then multiplied by two to acount for both feet steps. The double support ratio refers to the proportion of time in a gait cycle that both feet are in the stance phase to support the subject, whereas the single support ratio refers to the proportion of time in a gait cycle that only one foot touches the ground while the other is in the swing phase. Stance phase ratio refers to the proportion of time in a gait cycle that one foot is in the stance phase. All these features are summarized in Fig. 3.

E. Balance and Strength Features

We select two features in the balance and strength categories each. In the balance category, the maximum and minimum force differences between the medial (Meta12, Fig. 1) and lateral (Meta45, Fig. 1) sides of the forefoot in a gait cycle can be calculated as

$$\max_{i \subseteq \mathbb{I}} F_{M12}(i) - F_{M45}(i), \tag{2}$$

$$\min_{i \subseteq \mathbb{I}} F_{M12}(i) - F_{M45}(i). \tag{3}$$

These features can evaluate the capability of maintaining balance. The $\mathbb{I}$ refers to the set of indices i that belong to a gait cycle. Strength is quantified using the maximum force on the heel during heel strike and on the toe during toe off. All balance and strength features are normalized by the body weight to make them comparable among different subjects.

V. Multi-Task Feature Learning for Gait Disorder Diagnosis

Based on the extracted gait features, we diagnose gait disorders by constructing classifiers as functions of these features. In this work, we use an advanced multi-task feature learning (MTFL) classification method [34] to build three classifiers to discriminate gait observations of PD patients, and stroke patients, respectively, from those of healthy adults as well as between the gaits of PD and stroke patients. The selected learning strategies can be more feasible to identify similarities and differences of gait patterns than classic multi-class classification algorithms given multi-class classification methods focus on modeling only the exclusive (or discriminative) features of the different gait classes. Moreover, the methodology helps in important gait feature selection which may help in better understanding the key characteristics that distinguish abnormal geits and help in the target design of treatment.

MTL is a methodology that can improve the generalization of multiple related classification tasks by exploiting the task relationships, especially when the training set for some or all the tasks is limited. Related tasks are learned in a joint manner where the knowledge learned from one task may benefit learning for other tasks. For example, in gait disorder diagnosis the task of deciding if an observation, represented by a vector of gait features, is recorded from a PD patient or healthy subject, may help in diagnosing if another observation is recorded from a post-stroke patient or a healthy subject. MTL has been shown theoretically and empirically to be more effective than learning tasks individually [34]. A widely-used basic assumption is that the related tasks may share a common representation in the feature space, which is investigated by multi-task feature learning (MTFL).

We revisit two of our recently developed MTFL methods that both rely on a multiplicative decomposition of the model parameters used for each task, and hence are referred to as Multiplicative MTFL (MMTFL). Both methods are related to the widely used block-wise joint regularization MTFL method [35], but bring out a significant advantage over it in terms of selecting relevant features for classification. The new methods can simultaneously select features that are useful across multiple tasks and the features that might be only discriminative for a specific classification task.

Given T classification tasks in total, let $(\mathbf{X}_t \in \mathbb{R}^{\ell_t \times d}, \mathbf{y}_t \in \mathbb{R}^{\ell_t})$ be the sample set for the t-th task, where $\mathbf{X}_t$ is a matrix containing rows of examples and columns of gait features, $\mathbf{y}_t$ is a column vector containing the corresponding labels for each example, ℓ_t is the sample size of task t, and d is the number of features. We focus on creating linear classifiers $\mathbf{y}_t = sign(\mathbf{X}_t \boldsymbol{\alpha}_t)$ where $\boldsymbol{\alpha}_t$ is the vector of model parameters to be determined. We then define a model parameter matrix $\mathbf{A}$ where each column contains a task's parameter vector $\boldsymbol{\alpha}_t$, and thus each row of this matrix corresponds to a gait feature, i.e., the weights for a gait feature used for each of the T tasks, which we denote as $\boldsymbol{\alpha}^j$, and $j = 1, \cdots, d$. We choose a loss function $L(\boldsymbol{\alpha}_t, \mathbf{X}_t, \mathbf{y}_t)$ which typically measures the discrepancy between the prediction $\mathbf{X}_t \boldsymbol{\alpha}_t$ and the observation $\mathbf{y}_t$ for task t. In a classification task, the loss function is commonly a logistic regression loss.

The widely used block-wise joint regularization MTFL method solves the following optimization problem for the best $\boldsymbol{\alpha}$:

$$\min_{\boldsymbol{\alpha}_t} \sum_{t=1}^{T} L(\boldsymbol{\alpha}_t, \mathbf{X}_t, \mathbf{y}_t) + \lambda \Omega(\mathbf{A}), \quad t = 1, \cdots, T, \tag{4}$$

where $\Omega(\mathbf{A})$ is a block-wise regularizer, often called the $\ell_{1,p}$ matrix norm, that computes $\sum_{j=1}^{d} ||\boldsymbol{\alpha}^j||_p$. The common choice of p is 1, 2 or ∞. Minimizing this $\ell_{1,p}$ regularizer can shrink an entire row of $\mathbf{A}$ to zero, thus eliminating or selecting features for all tasks. The hyperparameter λ is used to play the trade-off between the loss function and the regularizer. However, the major limitation of the joint regularization MTFL method is that it either selects a feature for all tasks, or eliminates it from all tasks, which can be unnecessarily restrictive. In practice, several tasks may share features but some features may only be useful for a specific task. Hence we introduce the following multiplicative MTFL that addresses this issue.

A family of MMTFL methods can be derived by factorizing $\boldsymbol{\alpha}_t = \mathbf{c} \odot \boldsymbol{\beta}_t$, where $\odot$ computes a vector whose j-th component equals the product of $\mathbf{c}_j$ and $\boldsymbol{\beta}_t^j$, and in other words, $a_t^j = c_j \beta_j^t$. The vector $\mathbf{c}$ is applied across tasks, indicating whether certain features are useful to any of the tasks, and $\boldsymbol{\beta}_t$ is only relevant to task t. We relax the indicator vector $\mathbf{c}$ (i.e., a binary vector) into a non-negative $\mathbf{c}$ so the optimization problem can be tractable. If $c_j = 0$, then the j-th feature will not be used by any of the models. If $c_j > 0$, then a specific $\beta_t^j = 0$ can still rule out the j-th feature from the t-th task. We minimize a regularized loss function with separate regularizers for $\mathbf{c}$ and $\boldsymbol{\beta}_t$ as follows for the best models:

$$\min_{\boldsymbol{\beta}_t, \mathbf{c} \geq 0} \quad \sum_{t=1}^{T} L(\mathbf{c}, \boldsymbol{\beta}_t, \mathbf{X}_t, \mathbf{y}_t) + \gamma_1 \sum_{t=1}^{T} ||\boldsymbol{\beta}_t||_p^p + \gamma_2 ||\mathbf{c}||_k^k, \tag{5}$$

where $||\boldsymbol{\beta}_t||_p^p = \sum_{j=1}^{d} |\beta_j^t|^p$ and $||\mathbf{c}||_k^k = \sum_{j=1}^{d} (c_j)^k$, which are the ℓ_p-norm of $\boldsymbol{\beta}_t$ to the power of p and the ℓ_k-norm of $\mathbf{c}$ to the power of k if p and k are positive integers. The tuning parameters γ_1, and γ_2 are used to balance the empirical loss and regularizers. According to the different choices of p and k, we can have different levels of sparsity for $\mathbf{c}$ and $\boldsymbol{\beta}_t$.

The method MMTFL(2,1) refers to the case when $p = 2$ and $k = 1$ in Eq.(5) and solves a problem as follows:

$$\min_{\boldsymbol{\beta}_t, \mathbf{c} \geq 0} \quad \sum_{t=1}^{T} L(\mathbf{c}, \boldsymbol{\beta}_t, \mathbf{X}_t, \mathbf{y}_t) + \gamma_1 \sum_{t=1}^{T} ||\boldsymbol{\beta}_t||_2^2 + \gamma_2 ||\mathbf{c}||_1, \tag{6}$$

It is widely known that the ℓ_2-norm is not a sparsity-inducing norm, meaning that minimizing it will lead to a vector of many small entries that are however not exactly zero. Nevertheless, the ℓ_1-norm is a sparsity-inducing norm which creates a vector of many entries that are exactly zero. In Eq.(6), $\mathbf{c}$ is regularized by a sparsity-inducing norm, hence tending to eliminate many features from across all of the tasks. This formulation is more suitable for capturing the feature sharing pattern such that there exists a large subset of irrelevant features across tasks, requiring a sparse $\mathbf{c}$, but different tasks share a significant amount of features from the selected feature pool as indicated by $\mathbf{c}$, thus requiring a non-sparse $\boldsymbol{\beta}_t$.

The method MMTFL(1,2) is on the opposite direction when $p = 1$ and $k = 2$ in Eq.(5), and solves the following problem:

$$\min_{\boldsymbol{\beta}_t, \mathbf{c} \geq 0} \quad \sum_{t=1}^{T} L(\mathbf{c}, \boldsymbol{\beta}_t, \mathbf{X}_t, \mathbf{y}_t) + \gamma_1 \sum_{t=1}^{T} ||\boldsymbol{\beta}_t||_1 + \gamma_2 ||\mathbf{c}||_2^2. \tag{7}$$

Eq.(7) is suitable to capture a feature sharing pattern where none or only a small portion of the features can be removed because each may be useful for some tasks, thus requiring a non-sparse $\mathbf{c}$. However, different tasks share a small amount of these features, thus requiring a sparse $\boldsymbol{\beta}_t$. In this case, the ℓ_1-norm is applied to $\boldsymbol{\beta}_t$ where the ℓ_2-norm is applied to $\mathbf{c}$.

Since it is difficult to prove any relationship between gait features and actual gait problems; we hypothesize that these methods can help us identify the important gait features to recognize abnormal gaits due to the neurological diseases from otherwise healthy gaits, and may further locate features to discriminate between stroke-induced gaits and PD-induced gaits. To validate this hypothesis, in our performance evaluation, we compare the two methods against early MMTFL methods that are most comparable to the proposed methods and two baseline methods - single task learning (STL) methods that either use the ℓ_2-norm or the ℓ_1-norm to regularize individual $\boldsymbol{\alpha}_t$, which we referred to as STL-ridge and STL-lasso.

VI. Performance Evaluation

We designed two sets of experiments to evaluate the effectiveness of proposed methods. In the first set of experiments, we examined the classification Area Under the Curve (AUC) performance of the models created by different MTFL methods. In the second set of experiments we studied the importance of each proposed gait feature and their relevance to each classification task. In the following, we first describe our human participant study design and then present the experiment details.

A. Clinical Study Design

[To Wenlong: Do we need to rename this section and any references inside to human participant study?]

In order to evaluate the performance of the proposed algorithms, we collected GCF data using the developed smart shoes from healthy subjects without known walking problems and PD and post-stroke patients. Experiments with healthy subjects were conducted in the Mechanical Systems Control Laboratory at the University of California, Berkeley. The clinical study with patients was conducted in the William J. Rutter Center at the University of California, San Francisco (UCSF). The Committee on Human Research (CHR) at UCSF reviewed and approved this study. The original purpose of the clinical study was to examine whether patients could use visual feedback to direct their rehabilitation training and how was the training performance compared to traditional rehabilitation training directed by a physical therapist only. We use these datasets to evaluate the algorithm developed in this paper. Detailed experimental design and statistical analysis of the clinical outcomes are available in [36], [30].

To collect data for this work, the subjects were asked to walk multiple trials on a flat ground for at least 50 consecutive steps in their normal walking speeds. The data collected from five PD patients, three post-stroke patients, and three healthy subjects are used to test our methodology. The average ages for each of the groups are 69.2, 53 and 23 years old respectively. Representative raw data from each of the three groups are shown in Fig. 2. Gait features are extracted for each gait cycle and average results are taken for each trial. This generates a dataset of 180 observations with 21 features each.

B. Classification of Gait Disorders

To classify among stroke, PD and healthy gaits we designed and evaluated 3 classification tasks: healthy vs stroke gait, healthy vs Parkinson's gait and stroke vs Parkinson's gait. We compared our two new formulations MMTFL$\{2{,}1\}$ and MMTFL$\{1{,}2\}$ with other two standard MMTFL methods. They are summarized as follows:

- MMTFL$\{2{,}1\}$: formulation (6)
- MMTFL$\{1{,}2\}$: formulation (7)
- MMTFL$\{1{,}1\}$: formulation (5) with $p = k = 1$
- MMTFL$\{2{,}2\}$: formulation (5) with $p = k = 2$

In addition, two single task learning (STL) approaches were implemented as baselines and compared with the MTFL algorithms. They can be formulated as folows:

$$\min_{\boldsymbol{\alpha}_t} \sum_i ||y_t^i - X_t^i \boldsymbol{\alpha}_t|| + \lambda\Omega(\mathbf{a}_t), \quad t = 1, \cdots, T, \tag{8}$$

With X_t^i and y_t^i the i-th example and example label for task t, $\boldsymbol{\alpha}_t$ the parameter vector for task t, λ the hyperparameter used to play the trade-off between the least squares loss and the regularizer and Ω the selected regularizer. They are summarized as follows:

- STL_lasso: with $||a_t||_1$ as the regularizer
- STL_ridge: with $||a_t||_2^2$ as the regularizer

Before we run the experiments we used a tuning process to find appropriate values for the hyperparameters, γ_1 and γ_2. Grid search with three-fold cross validation (CV) was performed to select a proper hyperparameter value in the range from 10^{-3} to 10^3. In all the experiments, hyperparameters were fixed to the values that yielded the best performance in the CV.

In the first set of experiments, we partitioned the 180 observations into a training dataset and a testing dataset according to a given partition ratio, which was set to be 16%, 20%, 25%, 33% or 50%, respectively in each experiment. For each partition ratio, 10-fold CV was performed and average results were reported. The classification performance was measured using AUC, which measures the total area under the receiver operating characteristic (ROC) curves. Table II summarizes the results. We can observe from the results that MTFL methods always outperform STL methods. Specifically, with the smallest training set of 16%, the MMTFL$\{2{,}1\}$ method has the best improvement over the STL methods. When the training partition ratio was increased the AUC performance of all the methods improved consistently. When it reached 50%, STL or MTFL methods achieved their highest AUC scores, respectively. The advantage of MTFL methods in smaller training set ratios is explained because they can learn the tasks jointly and not exclusivelly, which is typically done in STL methods. On the other hand, along with the increase of training dataset percentage, more training examples were provided to the classifiers, making the classification easier and thus STL methods performed closer to MTFL when the partition rate increases.

Following that, we tested how well the classification generalizes when a new subject's gait was tested against a model built by gaits of other patients and healthy subjects. Specifically, the same classification tasks were performed with the same classification methods, but the testing data were from a single subject and all the data from the rest of subjects were used to train the corresponding model. We repeated this for each individual patient and healthy subject and the performance results are summarized in Table II, where average AUC is reported across all tasks and per task separately. PD, ST and H refer to the gait from PD patients, post-stroke patients and healthy subjects, respectively.

As can be observed from Table II, MTFL methods performed better than STL methods consistently. We also observe that there were some easier tasks (e.g., stroke vs healthy), where STL AUC scores were almost as good as MTFL ones, and some more challenging tasks (e.g., PD vs healthy), where STL AUC scores were worse compared to any other task.

To further study how the two new MTFL formulations perform on each task we report the confusion matrices of all the three tasks for MMTFL$\{1{,}2\}$ and MMTFL$\{2{,}1\}$ in Table III and IV respectively. Each row in the matrix corresponds to what gait was tested, while a column corresponds to what gait class the algorithm predicted. Between these two new formulations, MMTFL$\{1{,}2\}$ performed better with PD, as out of the 83 PD gaits that were tested MMTFL$\{1{,}2\}$ predicted 5 of them to be healthy gaits, i.e. false negatives, compared to 11 healthy gaits that were predicted by MMTFL$\{2{,}1\}$. MMTFL$\{2{,}1\}$ performed better with stroke, as out of the 31 PD gaits that were tested MMTFL$\{2{,}1\}$ predicted 3 of them to be healthy gaits, compared to 11 healthy gaits that were predicted by MMTFL$\{1{,}2\}$. Overall, MMTFL$\{2{,}1\}$ performed better, as it also achieved beter false positive rates. Specifically MMTFL$\{2{,}1\}$ predicted only 2 PD gaits out of 64 healthy gaits and 3 stroke giats out of the 83 PD gaits, compared to 5 and 7 predicted by MMTFL$\{1{,}2\}$ in the same tasks respectivelly.

The last set of experiments aimed to report the prediction results per patient, in order to give complete information of the performance of each subject's gait. Table V summarizes the per patient confusion matrices generated from MMTFL$\{2{,}1\}$ for the three classification tasks. The first column indicates each subject's disease or healthy condition and their identification numbers (ID) are given in the second column. The last two columns give number of times a trial was predicted to be PD, stroke or healthy subjects. The summation of these two numbers in each row corresponds to the total number of trials that were recorded for each subject. From the table we observe that stroke patient 4 was almost always predicted either healthy subject or PD patient, which means that her gait patterns were much different from other post-stroke patients. This patient was a 33 year old female with minor stroke, which explains the similarity of her gait to a healthy, when compared to other older stroke patients. This wrong prediction

	Random Partition					Testing a new subject			
Method	**16%**	**20%**	**25%**	**33%**	**50%**	All tasks	PD vs H	ST vs H	ST vs PD
MMTFL{2,2}	0.93±0.03	0.97±0.02	0.97±0.01	0.98±0.01	0.99±0.01	0.949	0.880	0.994	0.967
MMTFL{1,1}	0.94±0.04	0.96±0.02	0.98±0.01	0.98±0.01	0.99±0.01	0.979	0.982	0.993	0.960
MMTFL{2,1}	0.95±0.03	0.97±0.02	0.98±0.01	0.98±0.01	0.99±0.01	0.978	0.960	0.994	0.979
MMTFL{1,2}	0.93±0.04	0.96±0.03	0.98±0.01	0.98±0.01	0.99±0.01	0.975	0.983	0.983	0.967
STL_ridge	0.90±0.03	0.94±0.03	0.95±0.02	0.97±0.01	0.98±0.01	0.916	0.831	0.971	0.940
STL_lasso	0.92±0.03	0.96±0.02	0.97±0.02	0.98±0.01	0.99±0.00	0.944	0.893	0.977	0.961

TABLE II: AUC performance of different methodologies

	PD	Healthy
PD	78	5
Healthy	5	59

	Stroke	Healthy
Stroke	20	11
Healthy	0	64

	Stroke	PD
Stroke	25	6
PD	7	76

TABLE III: Confusion Matrices of **MMTFL{1,2}** for the 3 tasks, true labels in rows, predicted in columns

	PD	Healthy
PD	72	11
Healthy	2	62

	Stroke	Healthy
Stroke	28	3
Healthy	0	64

	Stroke	PD
Stroke	24	7
PD	3	80

TABLE IV: Confusion Matrices of **MMTFL{2,1}** for the 3 tasks, true labels in rows, predicted in columns

Subject		Predicted	
Disease	ID	PD	Healthy
PD	1	16	0
PD	2	11	6
PD	3	13	5
PD	5	19	0
PD	6	13	0
Healthy	7	1	22
Healthy	8	1	21
Healthy	9	0	19

Subject		Predicted	
Disease	ID	Stroke	Healthy
Stroke	4	4	3
Stroke	10	8	0
Stroke	11	16	0
Healthy	7	0	23
Healthy	8	0	22
Healthy	9	0	19

Subject		Predicted	
Disease	ID	Stroke	PD
PD	1	0	16
PD	2	0	17
PD	3	1	17
PD	5	2	17
PD	6	0	13
Stroke	4	1	6
Stroke	10	7	1
Stroke	11	16	0

TABLE V: Confusion Matrices of **MMTFL{2,1}** for the 3 tasks per patient

may also be related to the limited number of stroke paitents that participated in this study.

Given that MMTFL{2,1} performs best in general, the tested data seem to follow the assumption under which MMTFL{2,1} was designed. Specifically, across all three tasks there exists a large subset of irrelevant sensing features, requiring a sparce $\mathbf{c}$, but different tasks share a significant amount of features from the selected fetature pool as indicated by $\mathbf{c}$. In other words, there are some specific sensing features that help identify the neurological disorders. In the next subsection we are going to present the selected features for each method used in this paper.

C. Identification of Important Gait Features

Important gait features identified from gait disorder classification may help better understand the key characteristics that distinguish abnormal gait paterns among different gait disorders and healthy gait. They may also help the target design of treatment and evaluation of rehabilitative progress. In this subsection we present the important gait features that were identified by the used methods in our experiments, for each of the three classification tasks that were evaluated in subsection VI-B. With the important gait features we can understand which of the proposed gait features are more important to classify GCF data in stroke, PD or healthy classes. As described in section V for the MMTFL methods, we have $\boldsymbol{\alpha}_t = \mathbf{c} \odot \boldsymbol{\beta}_t$. The $\mathbf{c}$ vector is used across all tasks, indicating if a feature is useful for any of the tasks, and vector $\boldsymbol{\beta}_t$ is only for task t. Vector $\boldsymbol{\alpha}_t$ is the vector of model parameters for task t. In Fig. 4 we plot all vectors $\mathbf{c}$ for each MMTFL

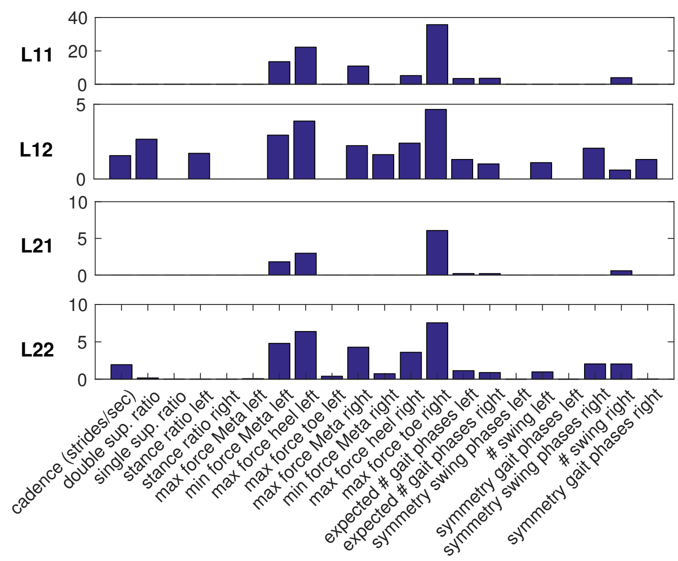


Fig. 4: Feature selection vector $\mathbf{c}$ from all MMTFL methods

model as progress bars to show the importance of each feature. In Fig. 5, 6, 7 we plot the learned task parameter vectors $\boldsymbol{\alpha}_t$ for each MMTFL and STL method for each of the three classification tasks.

Based on the general characteristics of Hemiplegic gait, most commonly seen in stroke, and Parkinsonian gait [5] we have the following observations:

- The most important feautre is the maximum force at the right toe and the second most selected feature is maximum force at the left heel. These two are strength in-

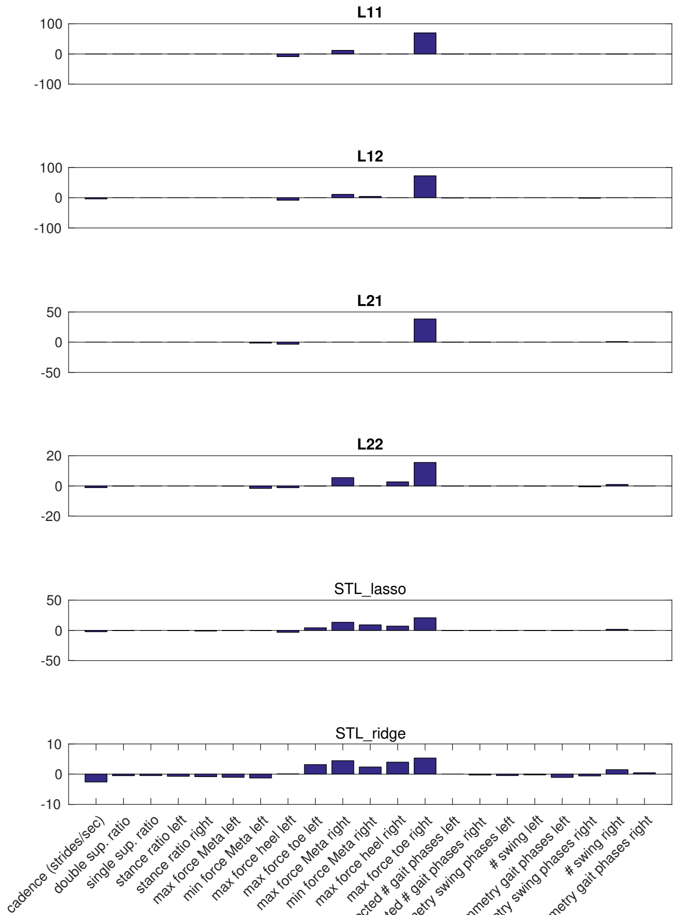


Fig. 5: Task parameter vector $\boldsymbol{\alpha}_t$ in the PD vs. healthy gait classification task.

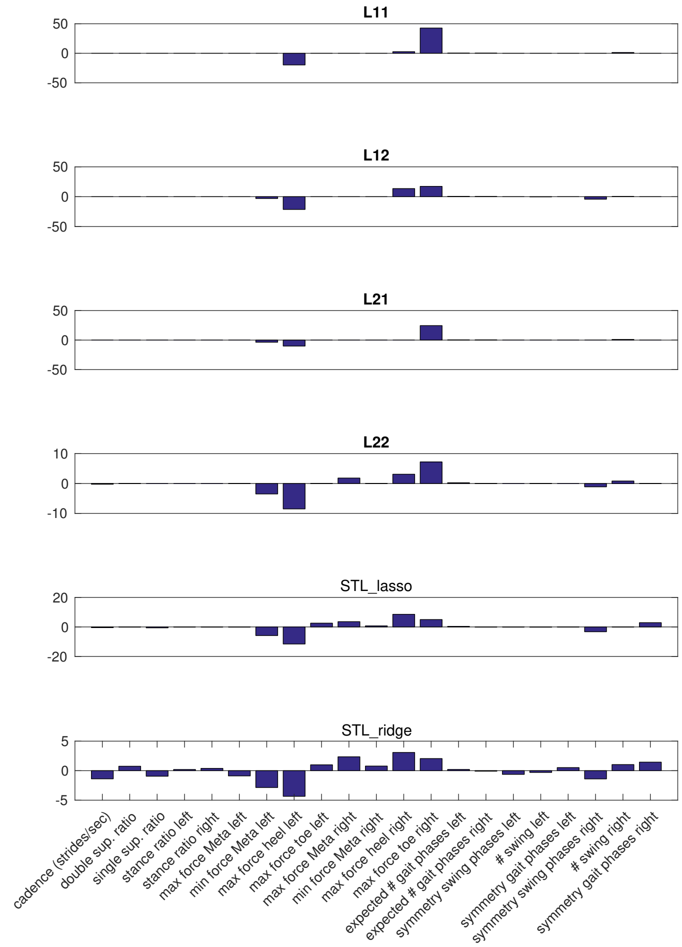


Fig. 6: Task parameter vector $\boldsymbol{\alpha}_t$ in the Stroke vs. healthy gait classification task.

dicators during toe off and heel strike gait phases. Patients with neurological related diseases, like stroke and PD, may experience weak muscle strength [5]. Circumduction of the affected leg in stroke can also produce different toe contact force signatures. Additionally, slow walking which is characteristic of both stroke and PD gait can have reduced force levels at the toe during push-off.

- Minimum force difference between medial and lateral sides of the metatarsophalangeal joints at the forefoot (see Sec. IV-E) at the left foot is another important feature, which is an indicator of balance. Rigidity, meaning stiff or inflexible muscles, is one of the main symptoms of PD, alongside tremor and slowness of movement. There is usually little or no arm swing to help in balancing the individual [5]. PD patients usually have reduced balance and the algorithm has identified this as an important feature.
- Cadence and double support ratio are mobility gait parameters and they are also important in distinguishing healthy vs pathological gait. As discussed before a common characteristic of stroke and PD subjects is their slow walking. This in turn affects the double support ratio.
- Symmetry of swing phases is found to be another important factor to distinguish pathological gaits. As discussed before, this parameter captures how evenly the swing gait phases are represented in the subject's gait. Circumduction of the affected leg can introduce additional gait phases and thus uneven representation of the detected swing phases.

All the rest features are not important and discarded by most of the models, except MMTFL{2,2}, which shows reduced sparsity. These findings are consistent with the literature about the characteristics of PD and stroke patient's gait [5].

VII. Conclusion

In this work, we presented the design of an algorithmic framework for gait disorder diagnosis to advance smart gait rehabilitation. Gait features were developed for different categories including mobility, balance, strength and gait phases. MTFL, an advanced classification method, was used to train the different classification tasks that can classify subject's gait. Data from Parkinson's and stroke patients, along with healthy subjects were used to evaluate the proposed methods.

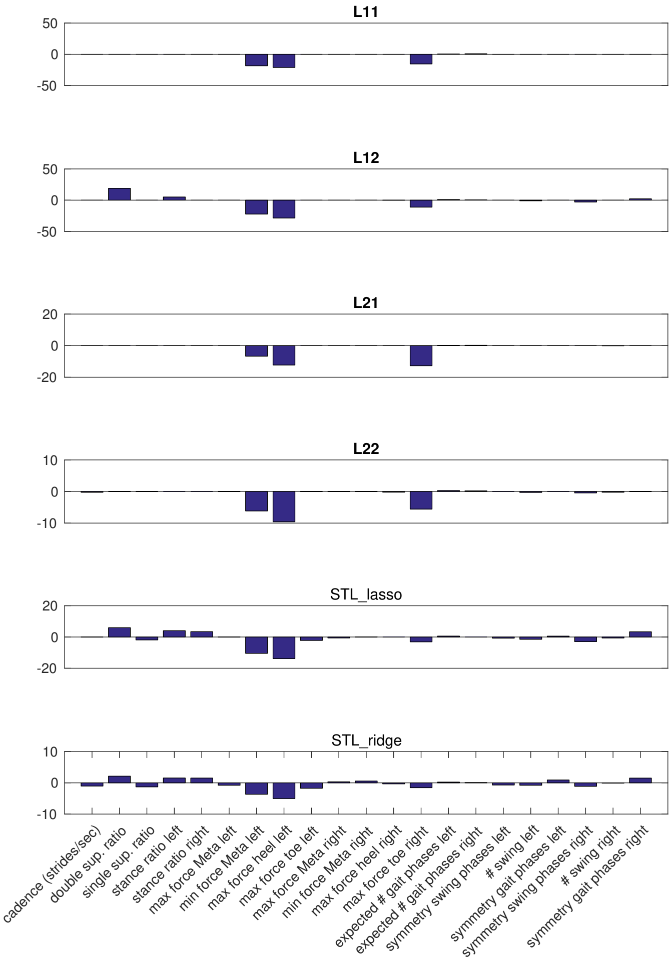


Fig. 7: Task parameter vector $\boldsymbol{\alpha}_t$ in the Stroke vs. PD gait classification task.

The proposed gait features successfully captured the underlying properties of each disease. MTFL was able to construct accurate classifiers based on the given gait parameters to distinguish abnormal gaits. Also it selected the most important gait parameters for this classification task, ignoring the rest. Selected features captured consistent characteristics of each disease with previous studies. This study demonstrated the potential to automate gait analysis of multiple common gait disorders which can benefit the medical professionals and patients with improved and targeted treatment plans for rehabilitation.

As future work, we intend to provide more advanced gait disorder diagnosis tools for more complex gait disorders that are difficult for the clinicians to detect and assist their assessment process in the clinic, evaluate these analytic methods and systems with properly designed clinical studies and design new methods for rehabilitation progress evaluation.

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