Feature Selection in Gait Classification of Leg Length and Distal Mass

Abstract

Technologies such as motion capture systems and force plates can aid in gait diagnosis and help identify the underlying differences between gait patterns. To support the most effective integration of these technologies in health professions, it is helpful to understand which features are most important in classification. Twenty individuals walked with combinations of an asymmetric leg length using a shoe with a small or large height and/or an asymmetric distal mass using a small or large ankle weight. These conditions changed the resultant gait of participants to impose asymmetric gait impairments. Different classifiers such as Support Vector Machines with Gaussian kernel functions were trained to classify leg length into 3 classes and distal mass into 5 classes using spatial-temporal, kinematic, and kinetic features, and evaluated for every combination of three features. Push-off force asymmetry was found to be an important feature in the classification of both leg length and distal mass. Asymmetry with regards to minimum knee angle, maximum hip extension, and the first vertical peak resulted in the best model for classifying leg length with an accuracy of 64.8%. Asymmetry with regards to braking force, push-off force, and vertical work resulted in the best model for classifying distal mass with an accuracy of 69.9%. The results suggest that the optimal features vary according to the specific impairment.

Keywords: Asymmetry, Gait, Feature Selection, Gait Impairments, SVM

1. Introduction

An individual's gait can be described quantitatively using various spatial-temporal, kinematic, and kinetic characteristics. For one gait impairment, some studies have compared the accuracy of models created using subsets of spatial-temporal, kinematic, or kinetic features [1, 2, 3, 4, 5, 6], and a few have further reduced the number of features necessary for classification [1, 2, 5]. The goal of this study is to compare the role of feature selection in gait classification among multiple, possibly overlapping, gait impairments. If there exists a representative subset of quantitative features that can be used to classify gait, the collection of these features can be implemented in the diagnosis of gait patterns and the subsequent rehabilitation efforts. The distinguishing features can reveal underlying similarities and differences between gait patterns.

Twenty individuals walked with combinations of an asymmetric leg length using a shoe with a small or large height and/or an asymmetric distal mass using a small or large ankle weight [7]. These conditions changed the resultant gait of participants to impose asymmetric gait impairments. The classification of leg length and distal mass is representative of the classification of different gait impairments. Clinically, the effects of leg length discrepancy have been studied [8, 9, 10], different masses on each leg occur in individuals with prosthetics, and both height and weight occur in therapies such as the Gait Enhancing Mobile Shoe [11, 12].

The features chosen for this project given in Table 1 are similar to the studies [13, 2, 5, 3, 1, 6, 4, 10]. However, instead of using the raw values of each metric, each feature reflects the asymmetry between the right and left side, similar to the asymmetry metric used by Khamis et al. [10]. Asymmetry is a means of classifying abnormal gaits that can transcend specific impairments. The same feature values are used to classify both leg length and distal mass to determine if there is consistency among the features important in gait classification.

2. Background

Gait is typically classified using either Support Vector Machines (SVM) or Artificial Neural Networks (ANN). The SVM algorithm determines a boundary between classes by minimizing the error function and maximizing the margin between the boundary and data points. The original features are implicitly mapped onto a hyperplane using a kernel function such as linear, Gaussian (radial basis function), or polynomial.

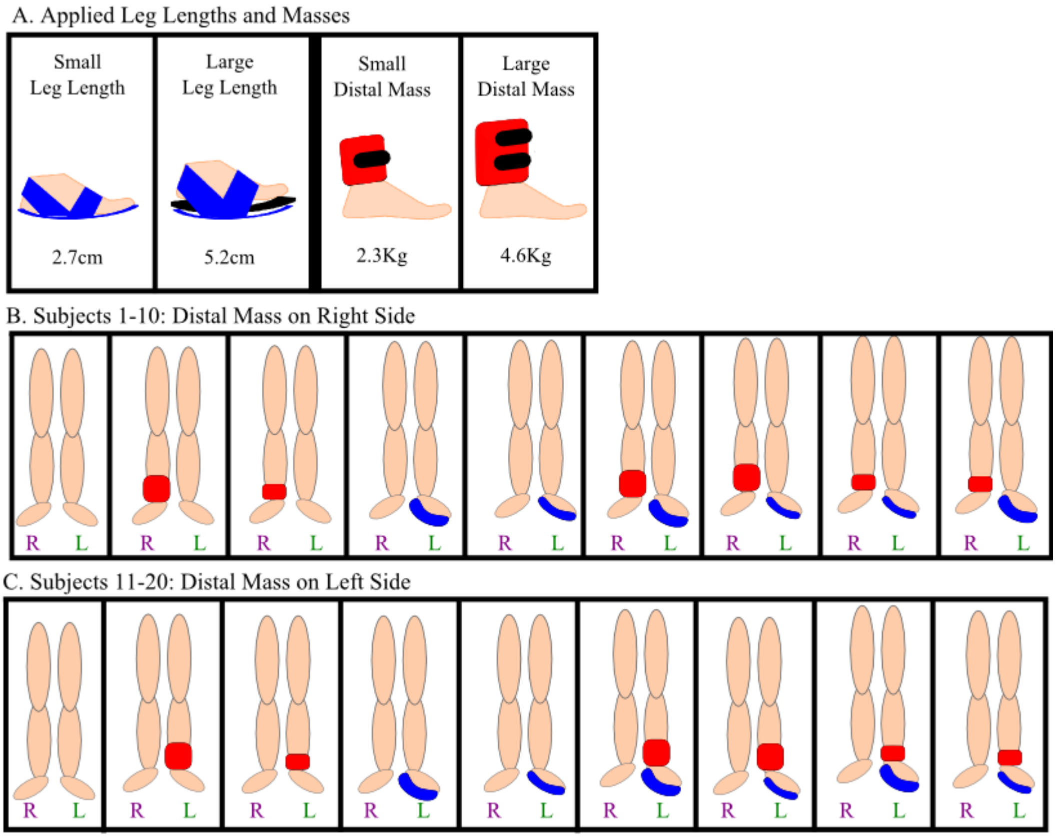

Figure 1: Experimental Procedure. Each experiment began and ended with normal walking without any perturbation. The order of leg length and distal mass perturbations shown in (B) and (C) were randomized. A small or large distal mass was added to the right leg for subjects 1-10 and the left leg for subjects 11-20. A small or large leg length was always added to the left leg with a shoe.

SVM has been successfully used to distinguish the gait pattern of the young vs. elderly [13, 2, 14, 15], cerebral palsy [16], Parkinson's disease [3, 5, 6, 17], autism [4], and patellofemoral pain syndrome [1]. The ANN algorithm passes the original features through layers of neurons, obtaining an associated weight for each neuron during training. Two studies that classify young and elderly individuals with both SVM and ANN algorithms found that the SVM model had higher accuracy [14, 13]. Ilias et al. found that the better model varied with the subset of features used and SVM with a Gaussian kernel function resulted in the best accuracy [4].

Gait classification of young vs. elderly individuals using SVM showed that just knee range of motion, horizontal peak push-off force, and normalized double support time provided better accuracy than all 24 features combined [2]. A subset of six features, braking and push-off vertical ground reaction peaks and four measures of time during the gait cycle, provided the best classification for individuals with Patellofemoral pain syndrome [1]. Step length, walking speed, knee angle, and vertical parameter of ground reaction force are significant features in ANN classification of Parkinson's disease [5].

3. Methods

The dataset used in this experiment was collected as part of a study conducted by Muratagic et al. (2017) which focused on the combined effects of leg length asymmetry and distal mass asymmetry. 20 subjects walked with each of the 10 perturbations shown in Figure 1. For each perturbation, participants either walked normally, or had some combination of an added distal mass (2.3kg or 4.6kg) and added leg length (2.7cm or 5.2cm). The twenty subjects (13 male, 7 female) had no physical impairments or difference in leg length greater than 2cm. The average height, weight, and comfortable walking speed was 1.785m, 82.8kg, and 1.22m/s respectively. Subject age ranged between

Table 1: Twenty-one spatial-temporal, kinematic, and kinetic features used in classification. The ankle angles are the angle between the toe, virtual ankle, and knee markers; the knee angles are between the ankle, knee, and hip markers; and the hip angles are between the knee, hip, and the horizontal axis.

Spatial-temporal Features	Step time – mode time per step during trial
	Step length – distance between heel markers at heel strike
Kinematic Features	Max ankle angle at maximum plantar flexion
	Min ankle angle at maximum dorsiflexion
	Ankle angle at heel strike
	Ankle angle at toe off
	Max knee angle (extension)
	Min knee angle (flexion)
	Knee angle at heel strike
	Knee angle at toe off
	Max hip angle (extension)
	Min hip angle (flexion)
	Hip angle at heel strike
	Hip angle at toe off
Kinetic Features	Vertical force first peak occurring at braking
	Vertical force second peak occurring at push-off
	Vertical force at dip occurring in the middle of stance phase
	Anterior–posterior braking force
	Anterior–posterior push-off force
	Vertical Work – area underneath vertical force graph
	Anterior–posterior Work – area underneath anterior–posterior force graph

18 and 30 years old and walking speed was determined by a 10m walk test. Nineteen of the twenty subjects were right leg dominant. The experimental procedures were approved by (university removed for blind review) Institutional Review Board. All subjects gave informed consent prior to participation in the experiment.

Figure 2: Computer Assisted Rehabilitation ENvironment (CAREN).

Data was collected using the Computer Assisted Rehabilitation ENvironment (CAREN) system, which is equipped with 10 motion capture cameras, a split belt treadmill, force plates, and a six degree of freedom motion platform. The forces exerted on the plates and the positions of eight markers placed at the base of the second toe, the heel, the center of rotation at the knees, and the internal/external center of rotation at the hips were recorded at a rate of 120Hz. In order to calculate ankle angles, a virtual ankle marker was placed one third of the distance from the heel to the toe. For each trial, up to 20 steps within 1ms in step time were chosen from the right and left sides. Twenty one characteristic features were extracted from each of the steps representing spatial-temporal, kinematic, and kinetic characteristics of gait shown in Table 1.

For each characteristic, the asymmetry between the median value on the right and left sides was computed. The difference between the values (right-left) was divided by the average of the two values. Once the features were extracted, 4 subjects were randomly selected to be the test dataset. The remaining subjects comprised the training dataset. The training dataset was standardized and principal component analysis performed such that more than 95% of the variance was retained. Principal component analysis was performed to reduce dimensionality. The same transformation coefficients found by standardizing and applying PCA to the training dataset were used to transform the test dataset.

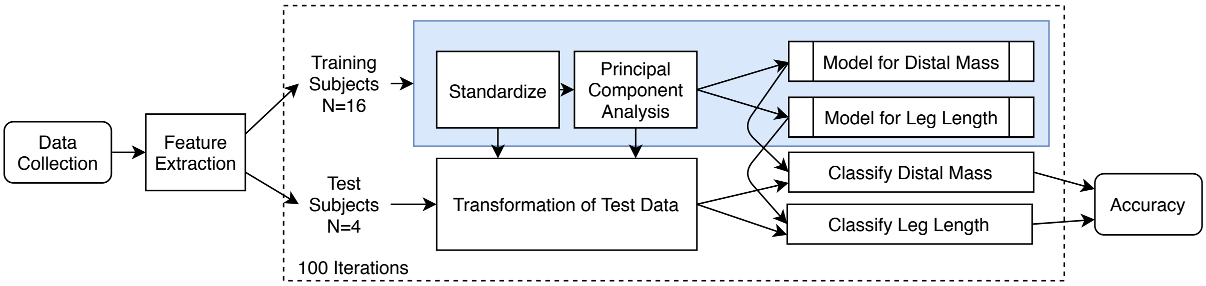

Figure 3: Schematic of Classification Methods.

Table 2: Percent accuracy and standard deviation results for many different classification algorithms for leg length and distal mass using all 21 features.

Model	Leg Length	Distal Mass
Logistic	70.2 (7.9)	64.3 (7.3)
SVM–linear	70.9 (8.9)	64.8 (7.1)
SVM–Gaussian	72.9 (8.8)	65.4 (7.0)
SVM–polynomial	70.9 (8.9)	66.3 (6.9)
Linear discriminant analysis	68.7 (8.0)	65.7 (6.9)
K-nearest neighbor–K=1	68.4 (8.9)	58.2 (5.6)
K-nearest neighbor–K=3	69.3 (9.4)	59.9 (6.0)
K-nearest neighbor–K=5	70.4 (8.5)	58.8 (6.4)
K-nearest neighbor–K=7	69.9 (8.3)	56.1 (6.3)
Naive bayes	64.0 (8.2)	51.6 (8.5)
Boosted Trees	62.7 (7.7)	49.8 (7.2)
ANN 1 neuron	63.2 (10.1)	61.6 (9.3)
ANN 2 neurons	62.9 (9.4)	60.7 (10.1)
ANN 3 neurons	60.6 (10.3)	56.2 (10.4)
ANN 4 neurons	61.0 (9.2)	56.6 (8.5)
ANN 5 neurons	60.7 (9.2)	55.0 (10.2)
ANN 6 neurons	61.2 (9.3)	55.7 (8.9)
ANN 7 neurons	58.9 (8.5)	54.2 (8.5)
ANN 8 neurons	58.8 (9.1)	53.8 (10.8)
ANN 9 neurons	59.1 (10.1)	51.1 (11.1)
ANN 10 neurons	59.5 (9.7)	51.2 (10.1)

Then, several classification models were trained in MATLAB using the Statistics and Machine Learning Toolbox, and the Neural Network Toolbox. Default settings of built-in functions are used unless otherwise noted. For the feedforwardnet function, we tried different combinations of number of hidden layers and number of neurons in each layer, however the results did not improve with the increasing number of hidden layers and number of neurons. Hence, we only present here the results for the two-layer neural network (i.e., one hidden layer) with 1-10 neurons in the hidden layer. Hyperbolic tangent is used as the activation function in neurons. The Levenberg-Marquardt backpropagation algorithm is used for training the neural networks. The entire process, which begins by randomly selecting 4 test subjects with 10 trials for each subject and includes standardization, PCA, and training and testing the classifier, was performed for 100 iterations and the accuracy computed. A schematic of the classification methods is shown in Figure 3.

To determine which features resulted in a model with higher accuracy, every combination of three features was tested with SVM with a Gaussian kernel function using the same method shown in Figure 3. Three features were chosen so that every combination could be tested in a reasonable time frame and to allow for

Table 3: Confusion tables for classification of leg length using SVM with a Gaussian kernel function using all 21 features. The table includes results from 4000 instances (100 iterations of 4 random test subjects with 10 trials for each iteration). The standard deviation in overall accuracy among the 100 iterations is given in parentheses. R-Right side L-Left side.

	True Leg Length Class			
Classification	None	Small	Large	Precision
None	1363	229	8	85.2%
Small	319	634	247	52.8%
Large	120	160	920	76.7%
			Overall Accuracy:	72.9 (8.8)%

Table 4: Confusion tables for classification of distal mass using SVM with a polynomial kernel function using all 21 features. The table includes results from 4000 instances (100 iterations of 4 random test subjects with 10 trials for each iteration). The standard deviation in overall accuracy among the 100 iterations is given in parentheses. R-Right side L-Left side.

	True Distal Mass Class					
Classification	R-Large	R-Small	None	L-Small	L-Large	Precision
R-Large	347	193	59	7	0	57.3%
R-Small	105	260	241	0	0	42.9%
None	11	140	1362	83	4	85.1%
L-Small	0	0	227	298	69	50.2%
L-Large	0	0	1	208	385	64.8%
					Overall Accuracy:	66.3 (6.9)%

some interaction between features.

4. Results and Discussion

The accuracy results for the many different classification algorithms for leg length and distal mass are shown in Table 2. SVM with a Gaussian kernel function had the highest accuracy for leg length and SVM with a polynomial kernel function had the highest accuracy for distal mass. Table 3 and Table 4 show the confusion tables for the SVM models with Gaussian and polynomial kernel functions respectively. The overall accuracy for three leg length classes was 72.9% and for five distal mass classes was 66.3%. For comparison, a study that classified healthy controls and four classes for functional impairments associated with the "hip," "knee," "ankle," and "calcaneus" using force plates found that SVM with a linear kernel function had an accuracy of 54.3% and SVM with a Gaussian kernel function had an accuracy of 51.2% [18]. Classification between three classes of gait (normal, distal mass, and leg length) using ANN and fast Fourier transformations resulted in an accuracy of 83.3% [19]. Using random forest to classify clinical patients with a longer left leg versus a longer right leg, accuracies of 64% and 80% were obtained for patients with and without additional musculoskeletal abnormalities respectively [10]. Studies classifying gait between two classes reported accuracies for Parkinson's disease of 87.5% [3], 95.63% [5], 98.2% [6], and 93.6% [17]; for cerebral palsy of 96.8% [16], for autism of 95.8% [4]; for patellofemoral pain syndrome of 88.89% [1]; for young vs. elderly of 90% [13], 100% [2], 90% [14], and 100% [15]; and for a healthy vs. impaired gait of 90.8% [18].

The intersectionality of the leg length and distal mass perturbations contribute both to the difficulty of classification and significance of the results, representing overlapping impairments. Differences between the gait produced by a 2.3kg ankle weight is more subtle than more extreme gait impairments such as Parkinson's disease. As such, because the differences in asymmetric gait patterns may not be immediately obvious to the untrained eye [20], its classification has more practical relevance in assisting in diagnosis.

Out of the 4000 instances tested, there were only 7 instances where the distal mass side (left vs. right) was misclassified. The accuracy of classification for no added asymmetries was the highest across both leg length and distal mass.

Figure 4 shows that the features that result in the most accurate three-feature SVM models with Gaussian kernel functions vary according to the impairment. For leg length, minimum knee angle, maximum hip angle at extension, and the first vertical peak formed the best combination of three features with an accuracy

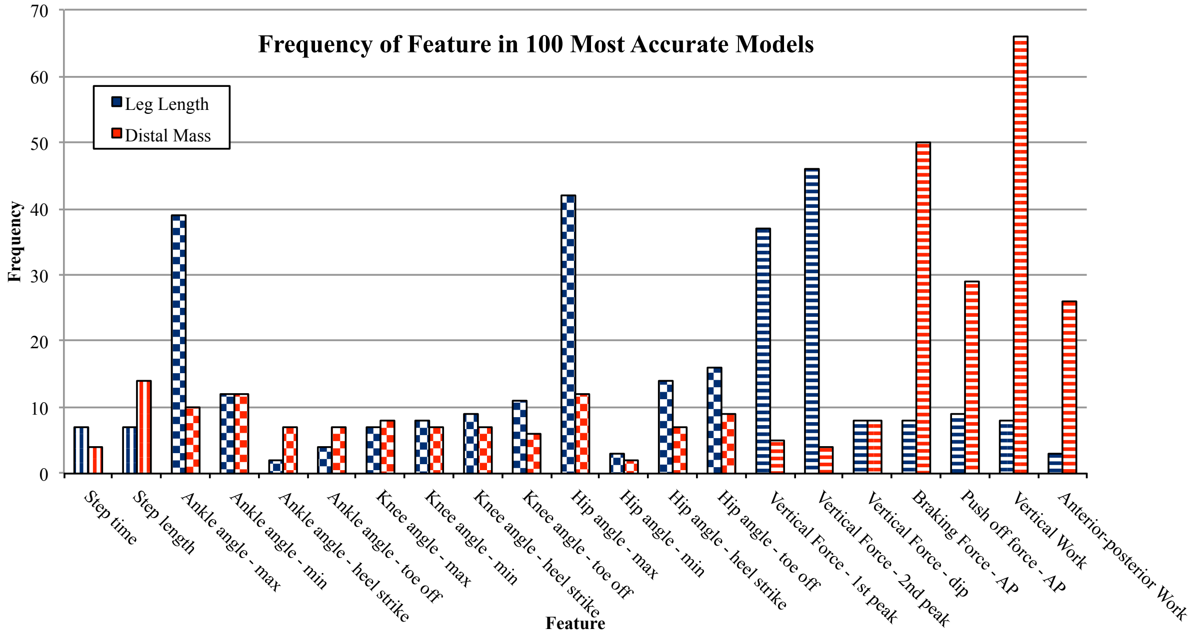

Figure 4: Frequency of each feature in the 100 most accurate three-feature SVM models with Gaussian kernel functions. All combinations of three features were tried for 100 iterations. Spatial-temporal features are shown in a vertical striped pattern, kinematic features in a checkerboard pattern, and kinetic features in a horizontal striped pattern. AP stands for anterior-posterior.

of 64.8%. For distal mass, braking force, push-off force, and vertical work formed the best combination of three features with an accuracy of 69.9%, higher than all 21 features combined. Those three features that resulted in the best model for distal mass, braking force, push-off force, and vertical work, resulted in only 40.3% accuracy for leg length. These features also differed from the previous studies using SVM to compare the gait of the young and elderly [2] and individuals with patellofemoral pain syndrome [1]. However some representation of the magnitude of the push-off force, either vertically (2nd peak) or in the anterior–posterior plane, was present in the best subsets of the two previous studies and found to be relevant in classification of both leg length and distal mass. For leg length, asymmetry between the vertical force second peak corresponding to push-off was present in 46 of the most accurate models. For distal mass, asymmetry between the anterior–posterior plane push-off forces were present in 29 of the most accurate models.

Models trained using only spatial-temporal features, kinematic features from motion capture data, and kinetic features from force plate data yielded accuracies of 32.9%, 55.9%, and 61.1% respectively for leg length and 43.7%, 43.0%, and 68% respectively for distal mass. A number of other studies have made a similar comparisons between all spatial-temporal features, kinematic features, and kinetic features [1, 2, 3, 4, 5, 6] with mixed results about relative importance. Direct comparison may be obscured by the possibility of models improving with smaller subsets of the three types of features (spatial-temporal, kinematic, and kinetic) and different impairments.

5. Conclusion

This study finds that reasonable accuracy may be achieved by only considering a few aspects of gait, and the same asymmetry features can be used to classify multiple gait patterns created by modulating leg length and distal mass. The second finding suggests that asymmetry could be used to classify and diagnose the many other gait patterns that involve significant asymmetry. While only kinetic features gathered from force plates classify distal mass better than all spatial-temporal, kinematic, and kinetic features combined, the same is not true for leg length. In leg length classification, the use of kinematic features in combination with kinetic features greatly improved accuracy. These findings intuitively match the kinematic nature of added leg length and the kinetic nature of added distal mass. Regardless, some representation of push-off force asymmetry was found to be an important feature in the classification of both leg length and distal mass. As these technologies become increasingly available to health professionals, it is important to consider the specific impairment during feature selection.

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