CLASSIFICATION OF HUMAN POSTURAL AND GESTURAL MOVEMENTS USING CENTER OF PRESSURE PARAMETERS DERIVED FROM FORCE PLATFORMS

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CLASSIFICATION OF HUMAN POSTURAL AND GESTURAL MOVEMENTS USING CENTER OF PRESSURE PARAMETERS DERIVED FROM FORCE PLATFORMS

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ABSTRACT

The human body, while standing, can be imagined as a complex feedback system that produces continuous sway patterns. Subtle body movements that can be caused by sensory cues such as visual or auditory, affective, cognitive, pathological or many other factors besides intended movements can be easily captured in the sway patterns derived from ground reaction forces and the body's center of pressure (COP). The purpose of this research is to classify human body movements, even the subtle movements, using a carefully selected feature set. For the first time, we propose a method to classify postural and gestural movements using data from force platforms collected from participants performing 11 choreographed movements. Twenty-three different displacement and frequency based features were initially extracted from COP time series, and ranking and wrapper methods were used for classification-guided feature extraction. Linear classifiers such as Fisher's Linear Discriminant analysis classifier and nonlinear classifiers such as nearest neighbor classifiers, support vector machines (SVM), and neural networks were explored and successfully applied to the aforementioned movement classification. The average classification rates on test sets ranged from approximately 79% to 92%. All the methods proposed in this experiment performed well by themselves over at least one movement type,

but none could outperform the others for all movement types and therefore a set of movement-specific features and classifiers is proposed.

APPROVAL PAGE

The faculty listed below, appointed by the Dean of the School of Computing and Engineering, have examined a thesis titled “Classification of human postural and gestural movements using center of pressure parameters derived from force platforms" presented by Sashi Saripalle, candidate for the Masters of Science degree, and certify that in their opinion it is worthy of acceptance.

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CHAPTER 1

BACKGROUND

Human motion detection has been an active topic of research for the past decade. This interest has been derived from wide applications of human motion detection such as motion detection, human identification and human behavior. I begin my discussion with motion detection using different platforms. I then review methods and goals studied using the data sets for respective platforms. Finally I discuss the data set used and how it differentiates from other data sets used in analysis of human motion detection.

As one of the prominent methods to track human motions, computer vision has been attracting many motion detection researchers due to its wide range of applications such as athlete performance analysis, video surveillance, perceptual user interface etc. (Liang et al. 2003). Computer Vision was significantly explored by researchers from over a decade. Aggarwal and Cai were one of the first to have relevant work done in motion analysis (Aggarwal & Cai 1996; Aggarwal & Cai 1999). They produced a number of surveys which cover human motion especially analysis involving human body parts, tracking moving human from a single view or multiple camera perspectives, and recognizing human activities from image sequences.(Liang et al. 2003) Moeslund and Granum presented a survey of computer vision based human motion capture. Its focus was on tracking, pose estimation and recognition (Moeslund & Granum 2001). The paper also briefly discusses about advancements of computer vision from 1990 to early 2000's. Also, future directions for Computer Vision based human motion detection were proposed in the paper. Ketcham illustrated human motion detection using seismic wave propagation where input signal is ground reaction force from a force platform.

Force platforms have widely been used for motion detection using ground reaction forces. Collins et al. have done extensive work in analyzing human stance on a force platform using force platform. There has also been a lot of research in aging, fall detection and postural sway using force platforms where the ground reaction forces were taken into consideration for motion analysis.

Almost any motion analysis can be generally broken into three phases – (a) Feature extraction, (b) Feature Selection (c) Motion classification. Different methods have been proposed from past decades to extract, rank and classify the features in the data set.

Serafeim et al. have done significant work where features were extracted using a Wavelet Packet (WP) transform algorithm in time-frequency domain using a two channel filter bank.

Qian et al. have derived features from 2D and 3D Center of Pressure (COP) trajectories. They made use of the pressure and position of the trajectories to identify a set of key points.

Robert et al. used footstep profile to derive the features of the signal. Footstep profile is a continuous time varying signal from the strike of the heel to the push of the toe on the load cell. It includes the strike of the heel, shift of the pressure from heel to toe and push of the toe which completes the profile.

Every platform used for motion analysis has data sets which consist of unique features. Computer vision for example uses cameras which can capture moving as well as standstill objects which have some movement. The data set then would contain the features of captured image being position of certain points. Similarly, a force platform being used for motion analysis would consider the ground reaction forces from the foot profiles or the COP trajectories or COP features. So, the data set depends on the goal of the project as well as the equipment used. The data set used in this research uses force plates which capture the raw COP patterns . Different

COP parameters are derived for the experiment from the raw COP patterns obtained. The feature extraction method will be discussed in detail in the forthcoming chapters

CHAPTER 2

INTRODUCTION

2.1 Science Team

As any other motion analysis research, this research was split mainly into three parts. Feature extraction, Feature ranking and selection, and human movement classification. Feature extraction part of the project was carried out by Mr. Gavin Paiva, Master's student in Mechanical Engineering Department, UMKC who derived the features from the COP signal and performed statistical analysis of the features. All credit for the traditional statistical analysis and feature extraction to Gavin.

Mr. Thomas Cliett III (Tom), undergraduate student in the Department of Computer Science Electrical Engineering, UMKC has analysed the performance of neural networks on the ranked features to classify different human movements.

I have done the feature ranking, feature selection and classification of human body movements which will be discussed in detail for the remaining of the document. I have also done the literature search on applications of force platform to detect human motion and also biometric personal identification using force platforms.

Dr. King helped me in literature search on Human Motor analysis using force platform. He also guided me regarding the scientific details of force platform used for the research.

Dr. Reza Derakhshani guided me throughout the project regarding the wrapper methods used. He also proposed the idea of using force platforms to detect human motions on which the research is mainly based upon.

Dr. Judee (University of Arizona, Tucson) and Dr. Lovelace choreographed the body movements which were performed by the subjects.

2.2 Machine Learning

Unarguably machines cannot exhibit intelligent behavior without the ability to learn. In fact it is proved by Turing's own model, the "*a*(utomatic)-Machine" model. Psychologists have long studied positive feedback models and reinforcement models as the basis of learning.

Expert systems in machine world can be perceived as rule based decision trees for answering complex decisions through simple solutions. One major disadvantage of these systems is the fact they make decisions on set of defined, unchangeable rules. This limitation has been overcome by designing memory models which dynamically update the rules of the system. The research is based on a sub-discipline of Artificial Intelligence (AL), a more robust modeling technique – Machine Learning (ML) which has its roots from Statistics. Machine Learning modeling techniques involve building memory-reinforced models from training data. The training data provides the priori information on a dataset which is used to calculate the Bayesian probabilities.

2.3 Motion Analysis

Although Computer Vision is making strides in motion analysis, it is restricted to certain rules. Computer vision cannot be used in light deprived environments where motion cannot be detected or even for subtle movements. It is very important that we have a reliable source of human motion scrutiny at all places irrespective of the environment and, force plates play a major role in providing the platform for human motion analysis at all places.

The human body can be imagined as a complex feedback system which maintains balance with the feedback signals. It has been proved that a body cannot be perfectly still- there is always a certain sway involved in the posture. The reflexive and voluntary movements play an

important role in this phenomenon. There is a significant difference in body's sway when a person has the eyes open while there is a visual feedback to the eyes close when there is no visual feedback.

The output signal of such a model using force platform represents ground reaction forces, movement, or sway, of the body's center of pressure (COP) position. We consider the COP features due to fact that that the COP is the measure of whole body dynamics. A plot of time varying coordinates of COP is defined as Stabilogram analysis. Stabilogram is a tool to investigate our complex human postural balance system, which is a measure of time behavior of COP signal. Stabilogram can be analyzed using different techniques to understand the postural control. Two such methods used widely are Stabilogram-Diffusion Analysis (SDA) and Deterended Fluctuation Analysis (DFA). Both methods are well suited to identify differences in postural stability. DFA provides a 'α' which gives information concerning correlation properties of signal. The deterended fluctuation function is obtained by comparing the actual signal with the corresponding deterended polynomial. As discussed above, the COP is a plot, jointly defined by Anterior- Posterior (AP) and Medial-Lateral (ML) coordinates. The initial AP and ML coordinates define the location of COP with respect to the center of the force platforms. These AP and ML are coordinates are used to calculate the measures COP parameters. As we know that COP based measurements defining postural steadiness are designed to depict wide range of aspects of stabilogram, we expect to see variations in these parameters with even a slightest change in postural movement.

COP position time series are extracted from force platform data and characterized using COP amplitude measures such as sway path, velocity, and area. Frequency measures including mean and median power frequencies and fractal dynamics measures including short-term and

long-term diffusion coefficients and Hurst exponents. In 1981, the International Society of Posturography suggested the use of two COP-based measures, mean velocity, and Root Mean Square (rms) distance, in their recommendations for standardizing force platform based evaluations of postural steadiness.

COP analysis, or posturography, has been used clinically to assess a variety of age- and disease-related balance deficiencies such as rehabilitation, human fall and balance recovery, peripheral neuropathy, stroke, and Parkinson's disease. Posturography may also present a non-obtrusive methodology for classifying body movements with applications ranging from Human Computer Interaction, or HCI (Shneiderman and Plaisant, 2009) to gait recognition for biometric identification (Sarkar et al., 2005). However, identifying patterns in COP data for use in posturography is tedious. Previous attempts at COP pattern recognition include template matching (Nakappan S. et al., 2006), statistical classification (Haibach et al., 2007; Santos et al., 2007), neural networks (Lafuente et al., 1998), and hybrid methods (Headon & Curwen, 2002), and focused on major movements with large variation such as crouching and jumping (Headon & Curwen, 2001; Headon & Curwen, 2002). While these movements were successfully classifiable with parameters extracted from force platform data, it is unclear whether similar parameters could be used to differentiate among delicate variation of ground reactions and thus generalized to a broader range of human standing movements, such as gesticulations and fine postural motions. To address the challenges of classifying multiple subtle movements, a detailed study of various feature selection and classification methods is needed.

Major factors in pattern recognition are feature selection and classifier design. For supervised feature selection, feature candidates should be evaluated relative to a quality metric, such as overall classification accuracy, sensitivity, specificity, or other classification-related

metrics such as the area under a receiver operating characteristics (ROC) curve (Guyon & Elisseeff, 2003; Jain & Zongker et al., 1997). During the classifier design step, different classification paradigms and their corresponding model-specific parameters need to be evaluated in order to find the optimal configuration (Alpaydin, 2004).

2.4 Objective Statement

As a preliminary step in using posturography for human motion recognition, the objectives of this study were to (1) determine which features are sensitive to differences in movement types using traditional statistical analyses, which also establishes the feasibility of the study; and (2) build feature vectors and classifiers to distinguish among these movements. It is hypothesized that a movement-specific, feature-classifier design will distinguish among movement types with higher predictive power in comparison to traditional statistical methodology. It is also hypothesized that multivariate interactions will need to be considered in the feature selection phase.

CHAPTER 3

METHODS

3.1 Hardware

AMTI OR6-6 force platforms were used to capture the forces and moments of a subject, using one force plate at a time. These force platforms were specifically designed for precise measurement of ground reaction forces, capturing the three orthogonal forces along the X, Y and Z axis and three moments producing a total of six outputs. A trial was captured for 1000 samples in a second.

3.2 Participants

Fourteen university students participated in this study. All participants were healthy and reported no conditions that would prevent them from standing for 20 minutes. All participants provided written informed consent and the project was approved by the Social Sciences Institutional Review Board at the University of Missouri – Kansas City.

3.3 Experimental Protocol

Data were collected in the Human Motion Laboratory at the University of Missouri – Kansas City. During each recording session, participants stood stationary on a force platform while performing movements in response to auditory cues (Figure 1). The movements consisted of 11 choreographed head (H), mid-body (MB), and postural (P) movements (Table 1), each performed continuously for 10 seconds. Measurements were made during four 10-second trials per movement, resulting in a total of 44 trials for each participant.

During each trial, forces and moments in the medial-lateral (ML), anterior-posterior (AP), and vertical directions were sampled at 1000 Hz from one AMTI OR6-6 force platform (AMTI; Watertown, MA, USA) connected to a computer running the Vicon NEXUS software (Vicon Motion Systems; Denver, CO, USA). Following data collection, NEXUS was used to calculate and export COP time series for each trial. COP signals were filtered using a second-order low-pass Butterworth filter with a cutoff frequency of 30 Hz. Initial AP and ML components of the COP (Figure 2) were set to 0 to remove offset caused by participants shifting position between trials.

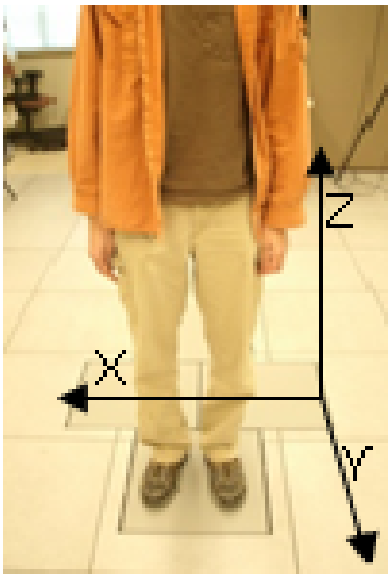

Figure 1: Testing configuration with coordinate directions

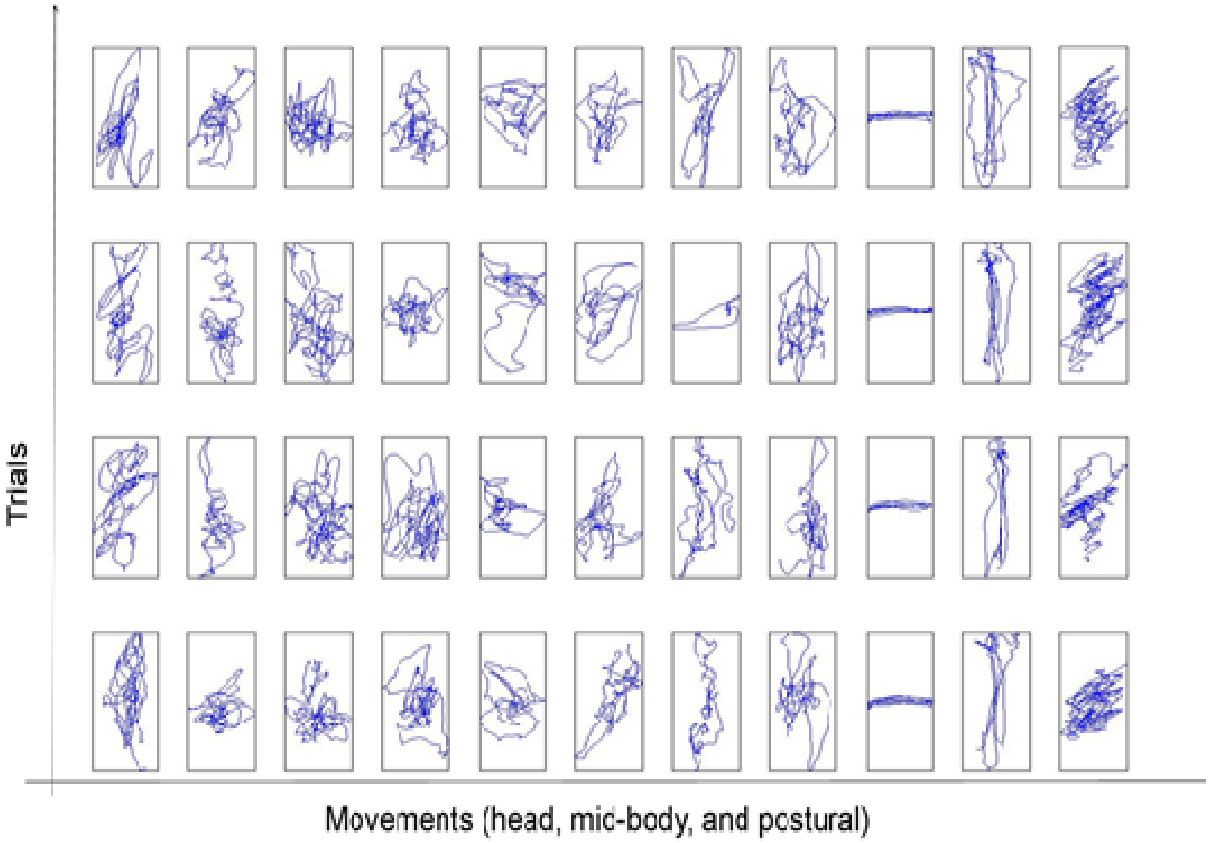

Figure 2: Representative COP trajectories showing 4 trials for each of 11 movements.

3.4 Description of Participant Motion

All the subjects were asked to perform eleven choreographed movements. Two movements were related to the upper body movement i.e. the head movements, represented by Mv1-H and Mv2-H. Six movements were related to the mid body (Mv3-MB through Mv8-MB) and three movements were related to the lower body movements (Mv9-P through Mv11-P). All the eleven movements were supervised by the data collector. The detailed list of movements is described in Table 1.

Table 1: Description of participant movements

Movement	Description
Mv1-H	Head nodding
Mv2-H	Head shaking
Mv3-MB	Shoulder shrugging without hand movement
Mv4-MB	Shoulder shrugging with palms turned upwards
Mv5-MB	Touching back of head
Mv6-MB	Touching one's nose
Mv7-MB	Scratching opposite arm
Mv8-MB	Hands outstretched
Mv9-P	Shifting weight from one foot to other
Mv10-P	Shifting weight to tiptoes
Mv11-P	Tapping foot

3.5 List of Feature Candidates

There are many features that can be derived from COP trajectory. But a thorough literature search indicated the best parameters from a COP trajectory (Santos et al., 2008; Carpenter et al., 2001; Vieira et al., 2009; Reilly et al., 2008; Maurer et al., 2005; Latash et al., 2003). 23 parameters were considered based on our review on all the parameters. All the features selected were positively inclined for our study i.e. they were movement sensitive and subject agnostic. All the parameters were mathematically easy to derive. Our final pool of COP features is described below.

Table 2: List of COP feature candidates

1	Standard deviation (SD) of COP segments	13	SD of velocity-AP
2	Path length	14	SD of velocity-ML
3	Sway-AP direction	15	Zero crossing rate-ML
4	Sway-ML direction	16	Mean velocity-AP
5	Velocity-Mean	17	Mean velocity-ML
6	Velocity-Max	18	Mean displacement-AP
7	Max displacement- AP	19	Mean displacement-ML
8	Max displacement- ML	20	Eccentricity
9	SD of displacement-AP	21	Length of major axis of instability
10	SD of displacement-ML	22	Angle of Major axis
11	Max velocity-AP	23	Median Frequency
12	Max velocity-ML		

Sway Parameters (3, 4): Sway is the net range of COP motion in AP and ML directions. Sway area is a measure of area covered by the COP path per unit time. Sway area depends on the parameters, distance from the Mean COP and the COP path length, and can be conceptualized as proportional to the product of mean distance and mean velocity.

Segment Length Parameters (1,2): COP segment lengths are the incremental displacements between pairs of points in the COP time series i.e. the root mean square (rms) distance is represented as the rms value of the distances from the mean COP to each pair of points in the initial AP and initial MP points. The rms distance along AP direction from the mean COP is represented as the standard deviation of the AP time series. Segment lengths are used to calculate standard deviation and summed to yield the COP path length

Displacement Based Parameters (7, 8, 9, 10, 18, and 19): Displacement is the distance from the mean COP location to each point in the COP time series. Parameters extracted from this data

include maximum value, mean value, and standard deviation in the AP and ML directions (Prieto et al., 1996).

Velocity Based Parameters (5, 6, 11, 12, 13, 14, 16, and 17): Velocities were calculated by numerical differentiation of the displacement-based parameters. These were used to calculate the maximum value, mean value, and standard of deviation with respect to the AP/ML directions and the total magnitude.

Elliptical Fit Based Parameters (20, 21, and 22): Several features can be calculated from an ellipse covering 85.35% of the sway area (Duarte & Zatsiorsky, 2002). The major axis corresponds to the direction of least stability. The eccentricity of the ellipse relates to the comparative directionality of the COP.

Frequency Parameters (15, 23): Median frequency of oscillation is the time frequency at which the integral of spectral power, calculated from the resultant COP vector, is one half the value of the total integral.

3.6 Data Analysis

MATLAB (The Math Works, Inc., Natick, MA, USA) was used for all data processing. Force platform data was digitally low-pass filtered using a second order Butterworth filter with a cutoff frequency of 30 Hz. Filtered data was further processed with a moment equilibrium analysis performed about the platform's coordinate axes, resulting in time series of two-dimensional coordinates representing the medial-lateral and anterior-posterior COP positions in the plane of the platform.

3.6.1 Statistical Analysis

There were two stages of statistical analysis performed - a traditional statistical analysis to evaluate significant differences among movement types; and an ensemble classification analysis to identify movement type.

Initial evaluation of COP measure performance was based on standard statistical analysis performed in the Minitab 15 software (Minitab, State Collage, PA). All analyses were performed with the movements as a fixed level factor and the subject identifier was treated as a random factor. While the p values computed from the subject identifier data may be skewed due to the non-random order of consecutive tests, it does provide some insight into the relative sensitivity of a COP measure to the two factors expected to be most significant. An initial MANOVA was performed on the gestural data, the postural data and the combined dataset and yielded the results that both the movements and subject were significant across the COP measures ($p<0.01$) in all cases. Further analysis was performed in the form of individual ANOVA's for each COP measure, eigenvector analysis of the MANOVA, and a partial correlation study based on the covariance matrix.

3.6.2 Feature Classification analysis

Using the COP feature candidates along with their corresponding known movements (labeled training data), sets of COP variables best suited to distinguish among movements were identified. Using the labeled training set, a range of classifiers were evaluated over different

sub-lists of ranked features to find the best feature-classifier arrangement with the highest discriminating power over each movement.

3.6.2.1 Feature ranking and selection

Supervised learning is a method of selecting feature candidates which can perform the desired pattern recognition by maximizing the quality metric (Guyon & Elisseeff et al., 2003; Jain & D. Zongker et al., 1997). This optimization process is a critical step in supervised pattern recognition, leading to better classification accuracy while reducing complexity (Jain et al., 2000).

One key issue in constructing feature vectors from a pool of candidate scalar features (Table 2) is the subset search and selection method. Ideally, given D feature candidates, 2^D-1 feature vectors need to be evaluated; an impractical choice for many problems (Jain& Zongker et al., 1997; Guyon & Elisseeff et al., 2003). Also known as wrapper methods, a group of suboptimal but faster solutions to this problem are based on non-exhaustive searches in a feature space guided by classifier feedback. One such method is univariate feature ranking and concatenation (henceforth referred to as feature selection A, or FS A), which works best when feature components are independent. An incrementally augmenting wrapper method builds feature vectors by starting from the top of a univariate ranked feature list, and concatenating elements until the classification metric of choice is optimized (Ruiz et al., 2006; Theodoridis & Koutroumbas, 2009). By evaluating groups of scalar features for the ranking stage, a variation of this method can incorporate some feature interdependencies. In this classification-guided subset search method, scalar features in randomly selected subsets that attain a minimum classification rate are ranked based on their frequency of appearance in the results pool. Higher-ranked scalar

features can then be combined by the aforementioned incremental feature vector building wrapper method (Li et al., 2004). This method is henceforth referred to as feature selection B (or FS B). Accordingly, in this study scalar COP features from Table 2 were first individually ranked and then grouped into vectors for best movement detection using different wrapper classifiers (FS A and FS B methods, Table 4).

To measure the quality of feature sets, correct classification rates, area under a ROC curve, sensitivity, and specificity were utilized (Alpaydin, 2004; Fawcett 2006; Príncipe, et al., 1994). A ROC is the plot of Genuine Accept Ratio (GAR) versus False Accept Ratio (FAR) (i.e. sensitivity versus 1-specificity), an important tool in the characterization of classifiers (Fawcett, 2006). This is especially important when dealing with unknown class distributions as in this study, where the area under the ROC curve (ROC AUC) provides a powerful scalar metric. When it comes to classification, it can be shown that regression-oriented error metrics, such as the mean squared error, contain half the information of a confusion matrix. Thus, sensitivity, specificity, and ROC AUC are more appropriate judges of classification (Baldi et al., 2000). ROC AUC and classification rates of nearest neighbor classifiers were used for the ranking stages of FS A and FS B, respectively. For FS B, a pool and subset size of 10, along with a subset selection threshold of 0.7 (training correct rate) were experimentally deemed to be the best choice in terms of overall results and computational footprint.

3.6.3 Classifiers

3.6.3.1 Linear Discriminant Analysis

Linear Discriminant Analysis (LDA) (Duda, 2001) is a linear supervised classification and dimensionality reduction method for casting multidimensional features into a single

dimension using a linear mixture. Suppose consider two classes and a D dimensional input vector X. Projection of X to one dimension can be done by using

$$Y=W^TX$$

Now, the two class problem can be classifiable by placing a threshold on 'Y' and defining the boundary. But sometimes projecting the classes onto one dimension can result in overlapping as shown in Figure 3.

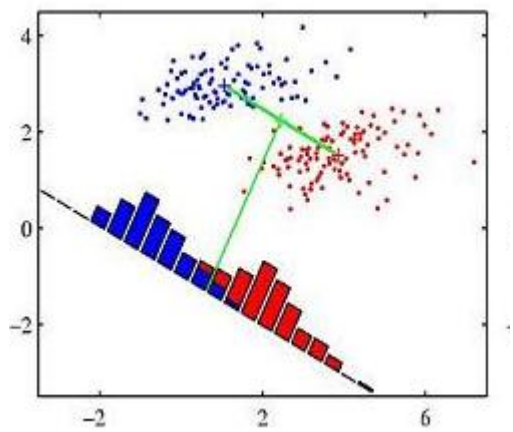

Figure 3: Classes projected on a single dimension plane

Christopher M. Bishop, *Pattern Recognition and Machine learning*, Springer (2006) (Location unknown) ISBN 0387310738

However we can overcome this problem by properly defining the weight vector 'W'. For example let us consider a two class problem where class 1 (C1) has M1 points and class 2 (C2) contains M2 points. The separation of two classes C1 and C2 can be measured when projected on '**W**' by the projected class means of C1 and C2 respectively. It can be defined as

$$m_2-m_1=W^T(m_2-m_1)$$

But in order to increase the separation between class means we can arbitrarily increase the magnitude of 'W'. To solve this problem we can fix 'W' to have unit length. Using Lagrange

multiplier, performing constrained maximization, we can derive a relation between ‘W’ and ‘**m**’ which shows that weight vector should be proportional to the line joining the center of mean’s of the two classes as shown in Figure 3. But, as we see the classes are not separated while projected into one dimension albeit being separated in their original two dimension space.

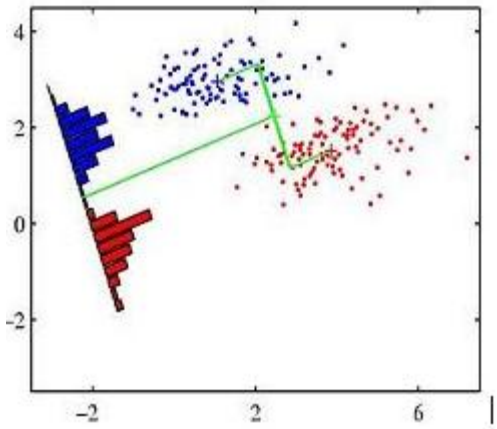

Figure 4: Projection based on Fisher’s linear discriminant

Christopher M. Bishop, *Pattern Recognition and Machine learning*, Springer (2006) (Location unknown) ISBN 0387310738

Fisher proposed that maximizing the class separation while also minimizing the class variance would produce minimum overlap. So after deriving the within class and between class covariance, we come up with a relation between ‘W’ and within class covariance which obeys fisher’s proposal. Fisher’s Linear Discriminant Analysis (LDA) is a special case of the quadratic boundary created by Bayes’ optimal classifier for normally distributed classes. Compared to other linear dimensionality reduction methods such as principle component analysis, LDA projections are usually better suited to classification.

3.6.3.2 Nearest Neighbor Classifier

The k nearest neighbor algorithm, or k-NN, classifies a data point by assigning it the label most frequently represented among the k nearest training data points (Bishop, 2006). Besides its speed, stability, and scalability, it can be shown that for large datasets the asymptotic classification error of k-NN approaches that of the optimal Bayes classifier for large k, and twice that figure for k=1 (Jiang & Zhou, 2004). An example of nearest neighbor classifier is shown in figure 6. Figure 6 shows a two class nearest neighbor classifier. Consider all dots to be Class 1 and all circles to be Class 2. If we consider the "data point 1" of Class 1, it is classified by drawing a boundary between itself and the nearest neighbors to it from the other class. However, k-NN is sensitive to outliers and noise, and thus it was used as one of the choices among other classifier candidates. In this study, k was set to 1 and the nearest neighbors were found using Euclidean distance measure given the satisfactory performance of this albeit simple setting.

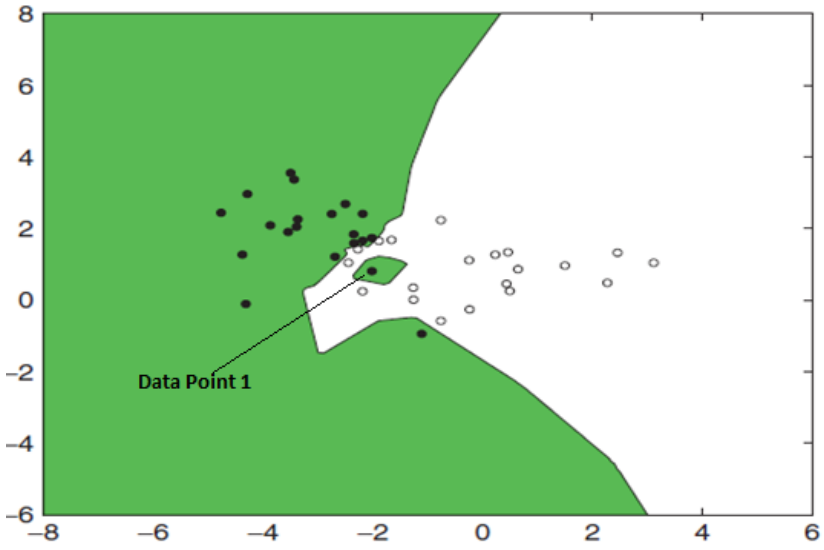

Figure 5: 1-nearest neighbor classifier

Lasse Holmstrom & Petri Koistin, *Pattern Recognition*, 06/03/2010, WIREs Computational Statistics, John Wiley & Sons inc., (Location Unknown)

3.6.3.3 Support Vector Machines

Support Vector Machines (SVMs) are maximum margin sparse kernel methods. They are widely used for classification and regression (Bishop, 2006; Vapnik, 2000). SVMs dichotomize labeled data by maximizing the distance of the decision boundary from the training samples that define the peripheries of the classes (support vectors). SVM kernel function matrices need to be positive semi-definite and symmetric (Burges, 1998). Popular examples of such kernel functions include Gaussian and polynomial formulations. Multiple instances of both kernels, with a range of different variances and orders, were used in this study. By introducing slack variables, one can make SVMs less sensitive to outliers by allowing misclassifications and soft margins. The penalty for allowing misclassifications is controlled by a parameter C, also known as the box constraint. Choice of C is important: smaller values allow for more slack and misclassifications, whereas larger C values push the SVM towards the strict maximum margin solution, which may cause over-training. Since the SVM objective function is quadratic and convex, its solution will be unique and global, and thus it does not suffer from local optima traps encountered by other nonlinear classifiers such as neural networks.

3.6.3.4 Neural Networks

Neural Networks (NN) were considered as another method for feature selection and classification, based on their nonparametric data-driven discrimination capabilities on datasets with unknown distributions (Haykin, 2009), and their reported successful applications in force plate signal identification (e.g. see (Lafuente et al., 1998)). Tom used feed-forward, single hidden layer neural networks with sigmoidal activation functions. Training and testing were carried out using early stopping and four-fold cross validation for better generalization and out of

sample performance estimation. The results of several randomly initialized gradient descent runs are then averaged together for a more accurate estimate of NN performance (Príncipe et al., 1999).

CHAPTER 4

RESULTS

4.1 Statistical Analysis of COP Features

ANOVAs performed on individual COP features indicated that movement produced a significant effect in all features. The analysis also revealed a wide range in ANOVA performance as R^2 values ranged from 2.51% to 91.55%. Table 3 shows the p-values of the factors (participant and movement) and the R^2 fit statistic showing how much of the data's variation traditional statistics were able to model. This analysis confirmed our conjecture on existence of movement specific, participant independent COP features and thus feasibility of the study, leading the way to the next objective.

Table 3: P-values for individual features from ANOVAs

Feature	Participant (p)	Motion (p)	R^2
1	<0.00	<0.00	77.77%
2	0.07	<0.00	56.32%
3	<0.00	<0.00	93.38%
4	<0.00	<0.00	91.44%
5	<0.00	<0.00	76.72%
6	0.26	<0.00	54.56%
7	<0.00	<0.00	91.55%
8	1.00	<0.00	12.05%
9	0.86	<0.00	66.84%
10	0.03	<0.00	32.52%
11	1.00	<0.00	17.51%
12	1.00	<0.00	13.89%
13	0.99	<0.00	3.15%
14	0.96	<0.00	2.51%
15	0.84	<0.00	60.39%
16	0.20	<0.00	33.80%
17	NA*	NA*	51.43%
18	NA*	NA*	11.45%
19	NA*	NA*	87.57%
20	<0.00	<0.00	37.67%
21	0.03	<0.00	14.94%
22	<0.00	<0.00	94.64%
23	0.36	<0.00	52.39%

* NA indicates p-values were numerically incalculable

4.2 Feature-Classifiers to Distinguish Among Movements

The following paragraphs exhibit results for our data-driven feature selection and classifier design, subsequent to the confirmation of movement-discriminating information among the COP feature candidates.

Feature ranking

Table 4 shows the cumulative ranking results for feature selection approaches FS A and FS B, where feature candidates (Table 2) are ranked according to their univariate or multivariate discrimination power over all the 11 movements. While also using the FS A approach, feature candidates were ranked using area under the curve (ROC) criteria and T-TEST criteria as shown in Table 4 and Table 5 respectively.

Table 4: Ranking of feature candidates using ROC criteria

Rank	Mv1	Mv2	Mv3	Mv4	Mv5	Mv6	Mv7	Mv8	Mv9	Mv10	Mv11
1	13	1	14	9	20	1	19	3	9	15	1
2	11	9	8	7	17	20	17	7	3	4	10
3	3	19	3	3	19	5	5	9	7	14	11
4	9	3	7	6	5	19	1	13	22	19	16
5	7	7	9	16	1	17	13	18	10	17	5
6	5	13	22	22	22	15	4	23	20	5	13
7	17	11	4	11	15	4	11	8	13	22	23
8	2	17	15	13	4	6	15	5	6	6	17
9	19	5	16	20	23	22	9	12	11	20	19
10	22	2	6	15	8	10	22	11	5	11	3
11	4	22	13	4	6	14	2	6	15	1	7
12	15	4	11	19	14	11	3	17	4	16	20
13	6	15	17	17	13	2	7	16	14	9	9
14	1	14	1	14	21	23	14	20	2	3	2
15	14	6	2	18	9	8	16	2	19	7	14
16	10	10	20	12	3	13	6	15	17	13	4
17	20	20	23	21	10	21	23	14	1	2	15
18	18	21	19	10	16	18	12	19	12	10	21
19	21	16	5	8	7	12	18	4	16	18	22
20	8	18	10	2	2	9	21	1	23	12	6
21	23	12	12	23	12	7	10	21	21	23	18
22	12	8	21	1	11	16	8	10	8	8	12
23	16	23	18	5	18	3	20	22	18	21	8

The above table shows the feature parameters rank for every movement albeit classification was done considering the ranked list averaged across the eleven movements.

Table 5: Ranking of feature candidates using T-TEST criteria

Rank	Mv1	Mv2	Mv3	Mv4	Mv5	Mv6	Mv7	Mv8	Mv9	Mv10	Mv11
1	13	2	22	22	5	2	2	22	7	4	10
2	11	13	20	20	23	5	19	2	3	14	16
3	9	19	8	13	19	19	5	17	9	15	1
4	3	5	14	2	2	13	13	19	10	19	19
5	2	11	13	11	17	22	17	23	13	2	17
6	7	17	2	7	11	17	11	13	2	16	11
7	5	7	11	3	13	11	22	9	22	17	5
8	17	22	7	5	1	1	4	1	6	22	2
9	19	3	3	9	4	4	1	8	11	5	13
10	22	1	5	15	6	15	15	6	8	13	22
11	15	9	4	4	3	6	3	20	23	11	8
12	4	4	9	6	15	10	9	15	5	8	23
13	1	15	15	1	7	9	14	3	20	6	21
14	6	14	6	19	9	3	6	5	1	1	6
15	14	8	17	14	20	8	8	16	14	3	14
16	20	20	1	17	14	7	16	11	4	12	15
17	8	21	23	21	22	21	21	14	17	23	20
18	21	16	21	23	21	16	23	7	21	9	15
19	23	23	16	18	16	18	20	21	12	18	4
20	16	12	10	12	12	12	10	12	19	10	7
21	10	10	12	16	10	20	18	10	18	20	3
22	18	6	19	10	18	23	12	18	15	7	18
23	12	18	18	14	20	8	8	16	14	21	12

Also, the gestural and postural movements were analyzed separately using both the criteria and postural movements were easily classified using any of the feature parameter. It is very important to analyze how the features are responding to different choreographed actions. It is

natural for the postural movements to be easily classifiable for they involve direct movement of legs. But gestural movements should be scrutinized to check for feature candidate validity to classify them optimally. Univariate feature selection was performed over all the features for the postural movements using both, area under the curve and T-TEST criteria. The results which are an average over all the eight movements are shown in Table 6.

Table 6: Univariate ranking for gestural movements using ROC and TTEST criteria

Rank	Features, FS A-ROC	Features, FS A-T TEST
1	23	8
2	14	10
3	16	20
4	10	14
5	19	11
6	13	19
7	17	1
8	18	16
9	11	13
10	5	6
11	6	22
12	12	3
13	1	9
14	2	2
15	4	15
16	7	21
17	9	5
18	3	17
19	15	8
20	20	12
21	21	4
22	22	18
23	8	7

The cumulative overall ranking across all the 11 movements for both FS A and FS B are shown here in Table 7.

Table 7: Overall feature ranks using univariate (FS A) and multivariate (FS B) classification-based assessments.

Rank	Features, FS A	Features, FS B
1	13	17
2	17	8
3	5	2
4	9	13
5	19	14
6	3	15
7	11	19
8	7	20
9	22	21
10	1	4
11	14	7
12	4	22
13	15	1
14	20	3
15	6	11
16	2	18
17	10	16
18	16	5
19	23	6
20	8	12
21	21	9
22	12	10
23	18	23

Movement-specific ranked lists, in conjunction with feedback from a variety of classifiers, were used in all the forthcoming wrapper methods to aggregate COP features into movement and classifier-specific input vectors.

4.2.1 Nearest Neighbor Feature Aggregation and Classification

Table 8 shows selected features and classification rates for each movement using a nearest neighbor classifier (kNN with k=1) for feature selection and classification. For each movement, scalar features were sequentially combined from the top of the corresponding ranked

list until the maximum four-fold cross validation classification rates were achieved. Depicted results are from FS B given the better outcome. As shown in Table 8, as well as in the following tables exhibiting LDA and SVM results, no single method can provide the best results for all 11 movements.

Table 8: Input feature vectors and classification results using the nearest neighbor method

Movement	Features	Correct Rate	Sensitivity	Specificity
Mv1-H	20,21,3,8,19,6,15,16,2,4,5,9 ,13,17,18,22,7,11,1,14,23,	0.8750	0.9357	0.2321
Mv2-H	20,9,7,4,18,22,3,5,6,8,19	0.8669	0.9196	0.3393
Mv3-MB	14,17,21,5,8,1,9,12,22,23,2	0.9773	1.0000	0.7500
Mv4-MB	1,19,3,8,15,7	0.9010	0.9393	0.5179
Mv5-MB	5,20,1,12,15,17,21,23,2,3,4, 6,9,11,13,16,18,8	0.8766	0.9250	0.3929
Mv6-MB	17,15,19,4,7,8,10,6,1,3,5	0.8945	0.9304	0.5357
Mv7-MB	6,19,3,8	0.8961	0.9518	0.3393
Mv8-MB	11,1,9,3,4,7,8,15,2,22,14,23	0.8815	0.9500	0.1964
Mv9-P	6,10,12,16,20,1,2,7,8,9	1.0000	1.0000	1.0000
Mv10-P	4,7,17,21,1	1.0000	1.0000	1.0000
Mv11-P	3,10,1,5,9,19	1.0000	1.0000	1.0000

4.2.2 LDA

Similar to the above, scalar features were sequentially and combined in order from the top of each movement-specific ranked list until the maximum four-fold cross validation classification rates were achieved. Depicted results are from FS B given the better outcome.

Table 9: Input feature vectors and classification using LDA

Movements	Features	Correct Rate	Sensitivity	Specificity
Mv1-H	20,21,3,8,19,6,15,16	0.6315	0.6071	0.8750
Mv2-H	20,9,7,4,18,22,3,5,6,8,19	0.6136	0.5821	0.9286
Mv3-MB	14,17,21,5,8	0.9773	1.0000	0.7500
Mv4-MB	1,19,3,8,15,7,11,14,16,21,5,6,9,10,22,2,4,12,17,18,23,13	0.5682	0.5393	0.8571
Mv5-MB	5,20,1,12,15,17,21,23,2,3,4,6	0.8247	0.8357	0.7143
Mv6-MB	17,15,19,4,7,8,10,6,1,3,5,9	0.7565	0.7518	0.8063
Mv7-MB	6,19,3,8,11,16,2,4,7,9,18,22,5,12,14,21,15,17,20,1,23	0.6396	0.6214	0.8214
Mv8-MB	11,1,9,3,4,7,8,15,2,22,14,23,6,10,13,18,19,17	0.6623	0.6625	0.6607
Mv9-P	6,10,12,16,20,1,2,7,8,9	1.0000	1.0000	1.0000
Mv10-P	4,7,17	0.9984	1.0000	0.9821
Mv11-P	3,10,1,5,9,19,20,21,7,14,17,2,4,13,15,23	0.9951	1.0000	0.9464

4.2.3 SVM

We explored a range of SVMs with different Gaussian and polynomial kernel functions. For both kernel types, the C-parameter varied from 0.01 to 200. For the Gaussian kernel, the sigma (spread) value was varied from 0.1 to 50. For the polynomial kernel, the order was varied from 2 to 8. It was observed that a C-parameter of 10 and a sigma value of 1; and a C parameter of 0.09 and a polynomial order of 4 provided better results for Gaussian and Polynomial SVMs, respectively. Again, for each movement, scalar features were sequentially combined from the top of their ranked list until the maximum four-fold cross validation SVM classification rates

were achieved. Ranked lists from FS A were used here as they provided better results (Tables 10 and 11).

Table 10: Input feature vectors and classification using Gaussian kernel SVM classifier

Movement	Features	Correct Rate	Sensitivity	Specificity
Mv1-H	13,11,3,9,7,5,17,2,19,22,4,15, 6,1,14,10,20,18,8,21,23	0.8003	0.8268	0.5357
Mv2-H	1,9,19,3,7,13,11,17,5,2,22,4,15,14,6,10,20	0.8133	0.8250	0.6964
Mv3-MB	14,8	0.9773	1.0000	0.7500
Mv4-MB	9,7,3,6,16,22,11,13,20,15,4,19,17,14,18,12,21	0.8490	0.8679	0.6607
Mv5-MB	20,17,19,5,1,22,15,4,23,8,6,14,13,21,9,3,10,16,7,2,12	0.8636	0.9018	0.4821
Mv6-MB	1,20,5,19,17,15,4,6,22,10,14, 11,2,23,8,13,21,18,12	0.8880	0.9232	0.5357
Mv7-MB	19,17,5,1,13,4,11,15,9,22,2,3,7,14,16,6,23,12,18,21,10	0.8198	0.8571	0.4464
Mv8-MB	3,7,9,13,18,23,8,5,12,11,6,17,16,20,2,15,14,19,4,1	0.8506	0.8857	0.5000
Mv9-P	9,3	1.0000	1.0000	1.0000
Mv10-P	15,4	0.9984	0.9982	1.0000
Mv11-P	1,10,11,16	0.9984	0.9982	1.0000

Table 11: Input feature vectors and classification using Polynomial kernel SVM classifier

Movement	Features	Correct Rate	Sensitivity	Specificity
Mv1-H	13,11,3,9,7,5,17,2,19,22,4,15,6,1,14,	0.6697	0.6268	0.8750
Mv2-H	1,9,19,3,7,13,11,17,5,2,22,4,15	0.7711	0.7768	0.7143
Mv3-MB	14,8	0.9773	1.0000	0.7500
Mv4-MB	9,7,3,6,16,22,11,13,20,15,4,19,17,14	0.8377	0.8429	0.7857
Mv5-MB	20,17,19,5,1,22,15,4,23,8,6,14,13,21 ,9,3,10,16	0.8555	0.8804	0.6071
Mv6-MB	1,20,5,19,17,15,4,6,22,10	0.8263	0.8339	0.7500
Mv7-MB	19,17,5,1,13,4,11,15,9,22,2,3,7,14,1	0.7179	0.7054	0.8393
Mv8-MB	3,7,9,13,18,23,8,5,12,11,6,17,16,20	0.7971	0.8943	0.6250
Mv9-P	9,3	1.0000	1.0000	1.0000
Mv10-P	15,4,14,19,17	1.0000	1.0000	1.0000
Mv11-P	1,10,11,16,5	1.0000	1.0000	1.0000

4.2.4 Neural Network Classification

The result of the Neural Networks for classification of the first 8 movements provided Equal Error Rate (or EER, a classifier operating point where sensitivity equals specificity) in the 0.30-0.39 range, which do not improve upon the results of other methods. The EERs for the last three movements were in the 0.1-0.03 range, but again were matched or outperformed by other methods, so neural networks were not pursued further.

4.3 Heterogeneous Classifier Bank

Considering the mixed performance of the examined classifiers across different movements, especially the first eight, it is better to “mix and match” classifier models by choosing the feature-classifier configurations that best detect each individual movement. This can be done by comparing all the corresponding rows from Tables 8 through 11, and selecting those models with

not only better correct classification rates but also balanced and acceptable sensitivities and specificities. The resulting heterogeneous classifier bank (Table 12) is best suited to classify all movements.

Table 12: Final feature-classifier selections with their test results

Movement	Ranking	Features	Correct Rate	Sensitivity	Specificity	Classifier
Mv1-H	FS A	13,11,3,9,7,5,17,2,19,22,4,15,6,1,14,10,20,18,8,21,23	0.8003	0.8268	0.5357	Gaussian kernel SVM
Mv2-H	FS A	1,9,19,3,7,13,11,17,5,2,22,4,15,14,6,10,20	0.8133	0.8250	0.6964	Gaussian kernel SVM
Mv3-MB	FS B	14,17,21,5,8	0.9773	1.0000	0.7500	LDA
Mv4-MB	FS A	9,7,3,6,16,22,11,13,20,15,4,19,17,14	0.8377	0.8429	0.7857	Polynomial kernel SVM
Mv5-MB	FS B	5,20,1,12,15,17,21,23,2,3,4,6	0.8247	0.8357	0.7143	LDA
Mv6-MB	FS A	1,20,5,19,17,15,4,6,22,10	0.8263	0.8339	0.7500	Polynomial kernel SVM
Mv7-MB	FS A	19,17,5,1,13,4,11,15,9,22,2,3,7,14, 16	0.7179	0.7054	0.8393	Polynomial kernel SVM
Mv8-MB	FS A	3,7,9,13,18,23,8,5,12,11,6,17,16,20	0.7971	0.8943	0.6250	Polynomial kernel SVM
Mv9-P	FS B	6,10,12,16,20,1,2,7,8,9	1.0000	1.0000	1.0000	Nearest neighbor
Mv10-P	FS B	4,7,17,21,1	1.0000	1.0000	1.0000	Nearest neighbor
Mv11-P	FS B	3,10,1,5,9,19	1.0000	1.0000	1.0000	Nearest neighbor

CHAPTER 5

DISCUSSION

Force platforms proved to be very useful for distinguishing the sway patterns obtained during the different body movements. Our methods seem to provide the necessary support to be useful in all aspects of analysis of body sway.

The statistical analysis shows that the COP parameters have the power to differentiate among the movements. They also seem to be participant sensitive i.e. they also have an ability to differentiate among the subjects who were performing the movements. This analysis leads to two different discussions. The first one being, there is an absolute necessity to perform multivariate feature selection and classification i.e. sometimes, features when used alone to classify among certain patterns would not perform very well. But, when they are properly grouped and used together they perform very well. The second discussion would be directed towards biometric application of force platforms i.e. the force platform being used to identify human subjects. Jain et al. have done relevant work towards the biometric application of force platforms. (Jain et al. 2003).

Unfortunately, the overall performance of the statistical analysis methods were questionable, as the assumptions for the statistical models, normal distributions and linear and independent effects, are only partially met. With the understanding that other methods such as those used in Objective 2 are better equipped to address these problems, traditional statistical methodology was not pursued further.

The machine learning methods were capable of performing multivariate feature selection and classification to varying extents. Feature selection B generally provided better performance for most classifiers, most likely due to its ability to reflect some of the multivariate interactions.

As expected, our results suggest that all classifiers performed well for the more pronounced postural movements Mv9-P through Mv11-P. However, the figures were mixed and generally not as high for more subtle gestural movements Mv1-H through Mv8-MB. Thus, for the following discussion, we will also report the overall average of the correct rates, sensitivities, and specificities of the gestural movements (gestural rate).

Nearest neighbor classifiers performed well with an average four-fold cross validation correct rate, sensitivity, and specificity of 0.92, 0.96, and 0.57, respectively (Table 5). Meanwhile, the average of the aforementioned figures for the gestural movements (gestural rate) was 0.75.

LDA classifiers performed only incrementally worse with an average four-fold cross validation correct rate, sensitivity, and specificity of 0.79, 0.78, and 0.85, respectively (Table 6). The corresponding gestural rate was 0.74. LDAs exhibited near singular covariance matrices for many feature subsets, particularly during multivariate feature selection, and thus nearest neighbor classifiers were used to process FS B. However, LDAs demonstrated an overall lower computational footprint.

SVM models performed better than other methods for most movements, with an average four-fold cross validation correct rate, sensitivity, and specificity of 0.88, 0.89, and 0.75; respectively (Tables 7 and 8). The corresponding gestural rate across all SVMs was 0.78, garnering them a larger presence in Table 9, which depicts the best feature-classifier set. SVMs' better performance, especially their more balanced sensitivity and specificity figures may be attributed to their nonlinear, maximum margin classification capabilities. As mentioned previously, the neural networks selected for this study did not outperform the other models across different movement types.

Especially when considering gestural movements, there was no single classifier or feature set that could outperform the rest when considering sensitivity and specificity in addition to mere correct rate, as the latter by itself can be a misleading figure in unbalanced, multi-class problems. Thus, using the best feature-classifier combinations from all the above methods, a heterogeneous bank of 11 classifiers was formed. To that end, the data from the different feature-classifier combinations (Tables 5 through 8) were pooled to yield the best selection by considering sensitivity, specificity, as well as overall gestural rates (Table 9). This observation calls for movement-specific feature sets and classifier designs as the best approach for Objective 2.

Because force platforms can conveniently and precisely produce sway and other motor related time series, this approach to measuring body movements can be advantageous when fast, unobtrusive, and automated evaluation of posturographic information is needed. For gait recognition or other applications in need of capturing body movements, force platforms may constitute a better input modality compared to video. For instance, conventional video feeds such as those garnered by security cameras cannot discern small or occluded movements, and face many challenges such as non-ideal lighting in real world scenarios. Human-computer interaction (Shneiderman and Plaisant, 2009) is another area in which force platforms could be used as an input modality in applications such as smart homes and video games (Betker et al., 2006; Orr & Abowd, 2000). Another application example comes from the area of deception detection. While it has been suggested that elements of gesture and posture may reflect deceptive intention (e.g., Frank & Ekman, 1997; Vrij, 2000), analysis of this information has usually relied on analysis of video records. Extracting features from videos, either by human observers (Sebanz & Shiffrar, 2009) or automated algorithms (Meservy et al., 2005) can be time-consuming and may miss subtle movements, especially those that occur tangentially to the plane of the video. Force plate

records, coupled with classifier analysis, could provide a more sensitive, automated indicator of postural correlates of deception or, indeed, any other cognitive state associated with postural changes.

CHAPTER 6

CONCLUSION

This study applied traditional statistical analysis and modern machine learning-based feature selection and classification techniques to detect differences in sway patterns associated with a variety of body movements captured by ground-embedded force platforms. As a result, a method was developed to successfully distinguish among COP patterns associated with various human movements. Classification-guided subset selection provided feature sets that, in conjunction with SVM, LDA, or nearest neighbor classifiers, provided average correct rates of approximately up to 92% across all 11 movements. Classification rates and especially sensitivity and specificity figures for different feature-classifier combinations varied highly for each movement, suggesting that use of single model or feature set is not sufficient for identification of all the movements studied. Linear classifiers performed rather poorly, suggesting that class boundaries among movements are nonlinear. SVMs had the highest overall performance of any individual classifier type on the grounds of highest individual sensitivity and specificity, especially for more subtle gestural movements. The fact that each movement required a specific classifier with its distinct multivariate feature set to achieve acceptable sensitivity, specificity, and classification rate indicates that a bank of movement-specific features along with their matched classifiers is best suited for identification of body movement based on force plate data.

CHAPTER 7

FUTURE WORK

As per statistical analysis, many features show sensitivity towards the subject participating in the movement i.e. the features are participant specific which can be used to analyze the biometric application of force platform to classify the subjects based on the feature set. A threefold cross validation was performed to test the authenticity of the data set to classify the subjects. After performing the threefold cross validation, the model was used to analyse the unseen or the test data which provided us with results shown in figure 6.

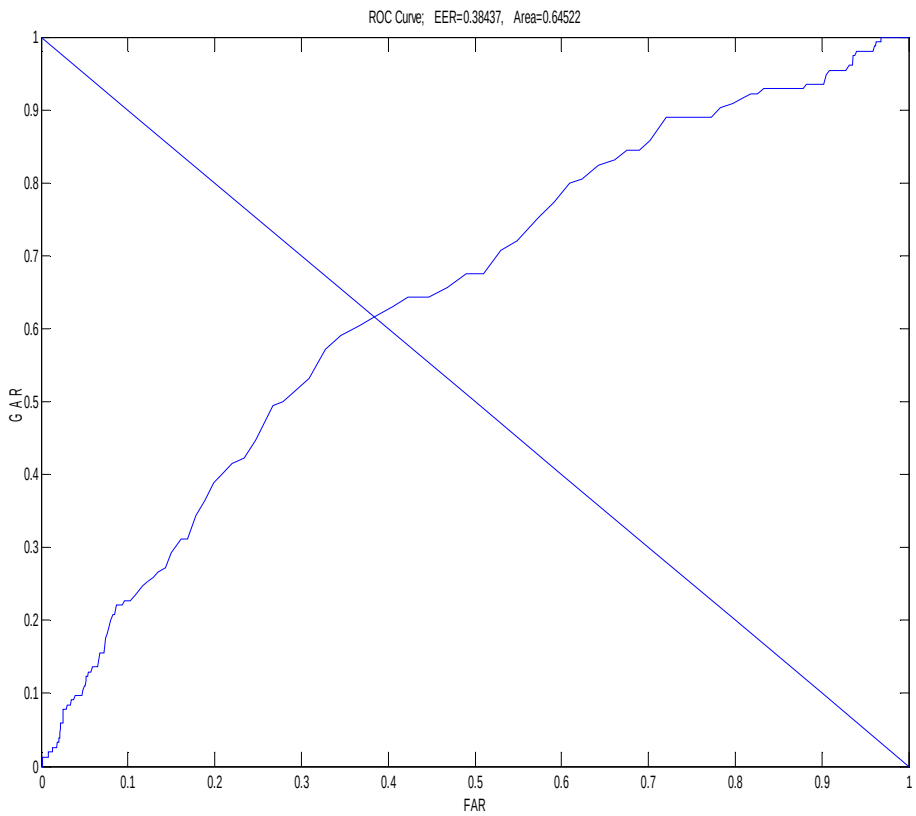

Figure 6: Plot of Fisher's LDA over all 23 features

The quality metric for measure of the fisher's LDA in my method is Area under the curve (ROC AUC). The Area under the curve is 64.55%.

A range of SVMs with different Gaussian and polynomial kernel functions were explored. For both kernel types, the C-parameter varied from 0.0001 to 10. For the Gaussian kernel, the sigma (spread) value was varied from 0.1 to 10. For the polynomial kernel, the order was varied from 2 to 10. All the results obtained were the best on 3 fold cross validation.

Table 13: Input feature vectors and classification using Gaussian kernel SVM classifier

Subject	Features	Correct Rate	Sensitivity	Specificity	Sigma	Box Constraint
Sub1	1-23	0.8117	0.8322	0.5455	1.9	0.008
Sub2	1-23	0.7208	0.7203	0.7273	3.4	0.09
Sub3	1-23	0.7013	0.6993	0.7273	3.3	0.003
Sub4	1-23	0.7792	0.7972	0.5455	2.5	0.05
Sub5	1-23	0.6498	0.9091	0.6782	2.6	0.02
Sub6	1-23	0.6039	0.6294	0.2727	3.3	0.01
Sub7	1-23	0.7597	0.7692	0.6364	4.9	0.10
Sub8	1-23	0.6948	0.6693	0.6364	4.4	0.01
Sub9	1-23	0.7013	0.7133	0.5445	3.6	0.007
Sub10	1-23	0.6818	0.6713	0.8182	3.3	0.002
Sub11	1-23	0.7273	0.7343	0.6364	3.8	0.006
Sub12	1-23	0.7792	0.8042	0.4545	4.5	0.01
Sub13	1-23	0.6818	0.6853	0.6364	4.9	0.1
Sub14	1-23	0.7857	0.8112	0.4545	2.2	0.001

Table 14: Input feature vectors and classification using Polynomial kernel SVM classifier

Subject	Features	Correct Rate	Sensitivity	Specificity	Order	Box Constraint
Sub1	1-23	0.8247	0.8531	0.4545	4	0.001
Sub2	1-23	0.7013	0.7133	0.5455	2	0.002
Sub3	1-23	0.6958	0.7063	0.5455	2	0.014
Sub4	1-23	0.7792	0.8112	0.3636	2	0.002
Sub5	1-23	0.7403	0.7962	0.3636	7	0.001
Sub6	1-23	0.5130	0.5175	0.4545	3	0.0002
Sub7	1-23	0.7078	0.6993	0.8182	3	0.001
Sub8	1-23	0.7468	0.7413	0.8182	3	0.001
Sub9	1-23	0.6364	0.6364	0.6364	3	0.026
Sub10	1-23	0.6364	0.6154	0.9091	3	0.002
Sub11	1-23	0.5195	0.5035	0.7273	2	0.003
Sub12	1-23	0.8831	0.9162	0.4545	2	0.003
Sub13	1-23	0.6623	0.6503	0.8182	2	0.001
Sub14	1-23	0.5974	0.6154	0.3636	3	0.100

The results obtained for the subject specific classification was not very robust albeit showing very impressive results for certain subjects. For example Subjects 2, 3, 10 were classified with a correct rate of 72%, 70%, 68% , sensitivities and specificities being 72%, 70% ,68% and 72%, 72%, 81% respectively. These results were pretty good considering the fact that all 23 features were used at once. A multivariate feature selection with a SVM would perform even better with at least a 5% increase in correct rate.

REFERENCES

Aggarwal, J.K., Cai, Q., 1999 Human motion analysis: a review, Computer Vision and Image Understanding, 73 (3) 428-440.

Aggarwal, J.K., Cai, Q., 1996. Tracking human motion using multiple cameras. Proc. of 13th Intl. Conf. on Pattern Recognition. pp. 68-72.

Aggarwal, J.K., Cai, Q., 1997 Human motion analysis: a review. Proc. of IEEE Workshop on Motion of Non-Rigid and Articulated Objects. pp. 90-102

Alpaydin, E., 2004. Introduction to machine learning. Cambridge. Mass. MIT Press.

Azevedo, T. M., Volchan, E., Imbiriba, L. A., Rodrigues, E. C., Oliveira, J. M., Oliveira, L. F., et al., 2005. A freezing-like posture to pictures of mutilation. Psychophysiology. 42, 255-260.

Baldi, P., Brunak, S., Chauvin, Y., Andersen, C. A. F., Nielsen, H., 2000. Assessing the accuracy of prediction algorithms for classification: an overview, Oxford University press, 16, 412-424.

Betker, A. L., Szturm, T., Moussavi, Z. K., Nett, C., 2006. Video game–based exercises for balance rehabilitation: A single-subject design. Arch Phys Med Rehabil. 8, 1141-1149.

Bishop, C. M., 2006. Pattern recognition and machine learning. New York: Springer.

Burges, C. J. C., 1998. A tutorial on support vector machines for pattern recognition. Data Mining and Knowledge Discovery. 2, pp.121-167.

Campbell, M. J., 2006. Statistics at square two: understanding modern statistical applications in medicine, 2nd ed. Blackwell, Malden, Mass.

Carpenter, M. G., Frank, J. S., Winter, D. A., Peysar, G. W., 2001. Sampling duration effects on center of pressure summary measures. Gait and Posture, 13, pp.35-40.

Collins, J. J., De Luca, C. J., 1993. Open-loop and closed-loop control of posture: a random-walk analysis of center-of-pressure trajectories. Exp Brain Res. 95, 308-318.

Collins, J. J., De Luca, C. J., 1995. Upright, correlated random walks: A statistical-biomechanics approach to human postural control system. Chaos. 5, 57-63.

Collins, J. J., De Luca, C. J., Pavlik, A. E., Roy, S. H., Emley, M.S., 1995. The effects of spaceflight on open-loop and closed-loop postural control mechanisms: human neurovestibular studies on SLS-2. Exp Brain Res. 107, 145-150.

Corriveau, H., Hebert, R., Raiche, M., Prince, F., 2004. Evaluation of postural stability in the elderly with stroke. Archives of Physical Medicine & Rehabilitation. 85, 1095-1101.

Corriveau, H., Prince, F., Hebert, R., Raiche, M., Tessier, D., Maheux, P., 2000. Evaluation of postural stability in elderly with diabetic neuropathy. Diabetes Care. 23, 1187-1191.

Cover, T.M., 1965. Geometrical and statistical properties of systems of linear inequalities with applications in pattern recognition. In IEEE Transactions on Electronic Computers.14, 326-334.

Diener, H. C., Dichgans, J., Bacher, M., Gompf, B., 1984. Quantification of postural sway in normals and patients with cerebellar diseases. Electroencephalogr Clin Neurophysiol. 57, 134-142.

Duarte, M., Zatsiorsky, V. M., 2000. On the fractal properties of natural human standing. Neurosci Lett. 283, 173-176.

Duarte, M., Zatsiorsky V. Z., 2002. Effects of body lean and visual information on the equilibrium maintenance. Experimental Brain Research. 146, pp. 60-69

Duda, R. O, Peter E. Hart and David G. Stork, 2001. Pattern Classification, 2nd ed. Wiley, New York.

Fawcett, T., 2006. An introduction to ROC analysis. Pattern Recognition Letters. 27, pp. 861-874.

Frank, M. G., Ekman, P., 1997. The ability to detect deceit generalizes across different types of high-stake lies. Journal of Personality and Social Psychology, 72, 1429-1439.

Guyon, I., Elisseeff, A., 2003. An introduction to variable and feature selection. J. Mach. Learn Res. 3, pp.1157-1182.

Haibach, P. S., Slobounov, S. M., Slobounova E. S., Newell, K. M., 2007. Virtual time-to-contact of postural stability boundaries as a function of support surface compliance. Exp Brain Res. 177, pp.471-482.

Hasan, S. S., Lichtenstein, M. J., Shiavi, R. G., 1990. Effect of loss of balance on biomechanics platform measures of sway: influence of stance and a method for adjustment. J Biomech. 23, 783-789.

Haykin, S. S., 2009. Neural networks and learning machines, 3rd ed. Prentice Hall, New York .

Headon, R., Curwen, R., 2001. Recognizing movements from the ground reaction force. ACM International Conference Proceeding Series. 15, 1-8.

Headon, R., Curwen, R., 2002. Movement awareness for ubiquitous game control. Personal and Ubiquitous Computing. 5-6, 407-415.

Horak, F. B., Dickstein, R., Peterka, R. J. 2002. Diabetic neuropathy and surface sway-referencing disrupt somatosensory information for postural stability in stance. Somatosensory & Motor Research. 19, 316-326.

Horak, F. B., Dimitrova, D., Nutt, J. G. 2005. Direction-specific postural instability in subjects with Parkinson's disease. Exp Neurol, 193, 504-521.

Jain, A. K, Duin, R. P. W., Jianchang, M., 2000. Statistical pattern recognition: a review. Pattern Analysis and Machine Intelligence. IEEE Transactions on Pattern analysis and Machine intelligence. 22, pp. 4-37.

Jiang, Y., Zhou, Z. H., 2004. Editing training data for kNN classifiers with neural network ensemble. Lecture Notes in Computer Science, 3173, pp. 356-361.

Lafuente, R., Belda, J.M., Sánchez-Lacuesta, J., Soler, C., Prat, J., 1998. Design and test of neural networks and statistical classifiers in computer-aided movement analysis: a case study on gait analysis. Clinical biomechanics. 13, 216-229.

Latash, M.L., Ferreira, S.S., Wieczorek, S.A., Duarte, M. 2003. Movement sway: changes in postural sway during voluntary shifts of the center of pressure. Experimental Brain Research. pp.314-324

Lehmann, J. F., Boswell, S., Price, R., Burleigh, A., deLateur, B. J., Jaffe, K. M., et al., 1990. Quantitative evaluation of sway as an indicator of functional balance in post-traumatic brain injury. Arch Phys Med Rehabil. 71, 955-962.

Li, L., Umbach, D. M., Terry, P., Taylor, J. A., 2004. Application of the GA/k-NN method to SELDI proteomics data, Bioinformatics. 20, pp. 1638-1640.

Maki, B. E., McIlroy, W. E., 1996. Influence of arousal and attention on the control of postural sway. Journal of Vestibular Research, 6, 53-59.

Maki, B. E., Holliday, P. J., Topper, A. K. 1994. A prospective study of postural balance and risk of falling in an ambulatory and independent elderly population. J Gerontol. 49, M72-84.

Maurer, C., Peterka, R.J., 2005. A new interpretation of spontaneous sway measures based on a model of human posture control. Journal of Neurophysiology. pp. 189-200.

Meservy, T. O., Jensen, M. L., Kruse, J., Burgoon, J. K., Nunamaker, J. F., Jr., Twitchell, D. P., 2005. Deception detection through automatic, unobtrusive analysis of nonverbal behavior. IEEE Intelligent Systems, 20, 36-43.

Mientjes, M. I., Frank, J.S., 1999. Balance in chronic low back pain patients compared to healthy people under various conditions in upright standing. Clin Biomech. 14, 710-716.

Moeslund, T.B., Granum, E., 2001. A survey of computer vision-based human motion capture, Computer Vision and Image Understanding, 81 (3) 231-268.

Murray, M. P. 1967. Gait as a total pattern of movement. Am J Phys Med, 46, 290-333.

Nakappan, S., Robinson, C.J., Darbhe, V.A., Storey, C.M., O'Neal, K.K., 2005. Variations in anterior-posterior COP patterns in elderly adults between psychophysically detected and non-detected short horizontal perturbations. Conf Proc IEEE Eng Med Biol Soc. 5, 5427-5430.

Nardone, A., Tarantola, J., Galante, M., Schieppati, M., 1998. Time course of stabilometric changes after a strenuous treadmill exercise. Arch Phys Med Rehabil. 79, 920-924.

Nardone, A., Tarantola, J., Giordano, A., Schieppati, M., 1997. Fatigue effects on body balance. Electroencephalogr Clin Neurophysiol. 105, 309-320.

Orr, R. J., Abowd, G. D., 2000. The smart floor: a mechanism for natural user identification and tracking. Conference on Human Factors in Computing Systems. 275-276.

Prieto, T. E., Myklebust, J. B, Hoffmann, R. G., Lovett, E. G., Myklebust, B. M., 1996. Measures of Postural Steadiness: Differences Between Healthy Young and Elderly Adults. IEEE Trans Biomed Eng. 43, 956-996.

Príncipe J. C., Euliano N. R., Lefebvre, W. C., 2000. Neural and adaptive systems: fundamentals through simulations. Wiley, New York.

Pudil, P., Novovi, J., Kittler, J., 1994. Floating search methods in feature selection. Pattern Recogn. Lett. 15, pp. 1119-1125.

Reilly, D.S., Van Donkelaar, P., Saavedra, S., Woollacott, M.H. 2008. Interaction between the development of postural control and the executive function of attention. Journal of Motor Behavior. pp.90-102.

Ruiz, R., Riquelme, J. C., Aguilar-Ruiz, J. S., 2006. Incremental wrapper-based gene selection from microarray data for cancer classification. Pattern Recognition, 39, pp. 2383-2392.

Santos, B.R., Delisle, A., Larivière, C., Plamondon, A., Imbeau, D., 2008. Reliability of centre of pressure summary measures of postural steadiness in healthy young adults. Gait & Posture, 27, pp. 408-415.

Sarkar, S., Phillips, P.J., Liu, Z.; Vega, I.R., Grother, P., Bowyer, K.W., 2005. The humanID gait challenge problem: data sets, performance, and analysis. Pattern Analysis and Machine Intelligence, IEEE Transactions ,27, pp.162-177

Schmit, J. M., Riley, M. A., Dalvi, A., Sahay, A., Shear, P. K., Shockley, K. D., 2006. Deterministic center of pressure patterns characterize postural instability in Parkinson's disease. Exp Brain Res. 168, 357-367.

Sebanz, N., Shiffrar, M., 2009. Detecting deception in a bluffing body: The role of expertise. Psychonomic Bulletin & Review, 16, 170-175.

Shneiderman, B., Plaisant, C., 2009. Designing the User Interface: Strategies for Effective Human-Computer Interaction, 5th ed. Addison-Wesley Publishing Co. Reading, MA. pp. 672.

Theodoridis, S., Koutroumbas, K., 2009. Pattern Recognition, 4th ed. Academic Press. Burlinglton MA.

Vapnik, V. N., 2000. The nature of statistical learning theory. 2nd ed. Springer, New York.

Vieira, V.M.M., Olivieira, L.F., Nadal, J. 2009. Estimation procedures affect the center of pressure frequency analysis. Brazilian Journal of Medical and Biological Research. pp.665-673.

Vrij, A., 2000. Detecting Lies and Deceit: The Psychology of lying and the implications for professional practice (1st ed.). New York: Wiley.

Wojcik, L. A., Thelen, D. G., Schultz A. B., Ashton-Miller, J. A., Alexander, N. B., 1999. Age and gender differences in single-step recovery from a forward fall. J Gerontol A Biol Sci Med Sci. 54, 44-50.

Wolff, D. R., Rose, J., Jones, V. K., Bloch, D. A., Oehlert, J. W., Gamble, J. G., 1998. Postural balance measurements for children and adolescents. J Orthop Res. 16, 271-275.

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