Ankle Fatigue Classification Using Support Vector Machines

[1]Jian Zhang, [1&2]Thurmon E. Lockhart, and [2]Rahul Soangra

[1] Industrial & Systems Engineering, Blacksburg, VA, USA
[2] School of Biomedical Engineering & Sciences, Virginia Tech-Wake Forest, VA, USA
email: zhangj@vt.edu, web: http://ise.locomotion.vt.edu

INTRODUCTION

Fall accidents are a significant problem for the elderly, in terms of both human suffering and economic losses. Localized muscle fatigue is a potential risk factor for slip-induced falls as muscle fatigue adversely affects proprioception, movement coordination and muscle reaction times leading to postural instability and gait changes. Specifically, fatigue in ankle is associated with decline in postural stability, motor performance and fall accidents in human subjects. Automated recognition of ankle fatigue condition may be advantageous in early detection of fall and injury risks. In this study, we explore the classification potential of support vector machines (SVM) in recognizing gait patterns associated with ankle fatigue utilizing an inertial measurement unit (IMU) as the wearable technology has the potential to investigate continuous kinematic changes evoked by fatigue.

The SVM is considered a powerful technique for general data classification and has been widely used to classify human motion patterns with good results. The advantage of SVM algorithm [1] is that it can generate a classification result with limited data sets by minimizing both structural and empirical risks. Although numerous studies have been devoted to improving the SVM algorithms, little work has been performed to assess the robustness of SVM algorithms associated with movement variations and fatigue states.

In the current study, we aim to monitor kinematics of walking in unconstrained environments using an IMU situated around the trunk Center-of-Mass (COM) during ankle fatigue and no-fatigue walking conditions. We hypothesize that ankle fatigue will influence walking behavior and this subtle changes in gait can be classified by supervised machine learning techniques such as support vector machines.

METHODS

Seventeen healthy young adults (9 males and 8 females) participated in the study. The participants mean age was 29±11 years, height 174±10 cm, and weight 73±12 kg. The experiment was composed of inducement of fatigue in ankle joints with squatting exercises [2]. Walking trials were conducted both prior and after the fatiguing condition. The IMU node consisted of MMA7261QT tri-axial accelerometers and IDG-300 (*x* and *y* plane gyroscope) and ADXRS300, *z*-plane uniaxial gyroscope aggregated in the Technology-Enabled Medical Precision Observation (TEMPO) platform which was manufactured in collaboration with the research team of the University of Virginia [3].

For the classification, both training and testing data sets consisted of ankle fatigue/no-fatigue walking data. Kinematic data used for SVM input was Representative Gait Cycle (RGC) data. RGC begins when one foot contacts the ground and ends when that foot contacts the ground again using the shank IMU. A perfect representative gait cycle signal between two easily identifiable events of the same foot was chosen for the analysis (Figure 1). This representative gait cycle started at peak right shank angular velocity (left foot mid-stance) and terminated at consecutive peak right shank angular velocity (left foot mid-stance). All IMU signals were truncated to RGC and normalized to 0% to 100%. A repeated-measure design was used to test changes intra-subject in gait parameters from normal walking and post fatigue walking trials.

The SVM classifier has not been applied previously to ankle fatigue and no-fatigue gait patterns. An important characteristic of using SVM classifier in this study was to obtain high ankle fatigue/no-fatigue classification accuracy with three different types of feature input (Table 1): (1) selected “ad hoc” features based on domain knowledge; (2) general features; and (3) concatenated complete gait pattern signals. After extracting features, all features or input variables were normalized by computing their z-scores. Input data was kept in range between 0 and 1. Then Principle Component Analysis (PCA) was employed to decrease the dimensions. The objective of PCA is to perform dimensionality reduction while preserving as much of the randomness in the high-dimensional space as possible. Subsequently, a five-fold cross-validation scheme was adopted to evaluate the generalizability of the SVM classifier. Finally, SVM models were trained over the range $C=2^{-10}$ to 2^{10} using linear, polynomial and radial basis function kernel.

RESULTS AND DISCUSSION

The machine learning classification results demonstrated high intra-individual classification rates across all three-kernel types (i.e., linear, polynomial and radial basis function kernel). We found that linear (accuracy ~97-99%) and RBF (accuracy ~96-98%) kernels perform equally well in intra-individual ankle fatigue/no-fatigue classifications (Table 2). The polynomial kernel had the lowest classification accuracy amongst all three different types of kernels. Our results also indicate that ankle fatigue effects are evident in individuals’ gait patterns and extracted features and, SVM accurately classified ankle fatigue/no-fatigue conditions. We found that SVM classifier incorporating trunk kinematic signals during gait has an excellent potential to predict fatigue status intra-individually (~98% accurate predictions).

Previous researchers have adopted various gait feature extraction methods for SVM classification. Results of our investigation indicate that features extraction methods influenced classification accuracy. In ankle fatigue classification, concatenated waveform input resulted in the highest classification accuracies; however, selected feature input had better classification accuracies than general feature input. This may be attributed to intra-individual variability. In essence, concatenated waveform input exhibited superior classification accuracy and had important gait information to classify fatigue; on the contrary, the other two feature extraction methods lacked peculiar information relevant to achieving higher classification results.

Three different types of kernels were employed in SVM: linear, polynomial, and radial basis function. Both linear and RBF kernels performed well in ankle fatigue/no-fatigue classifications. Considering the computational cost, RBF and polynomial kernels need less time compared to linear kernels in the same conditions. As such, RBF kernel is the most promising kernel function in the ankle fatigue classification schemes, and it may also provide better applicability to real time system implementation.

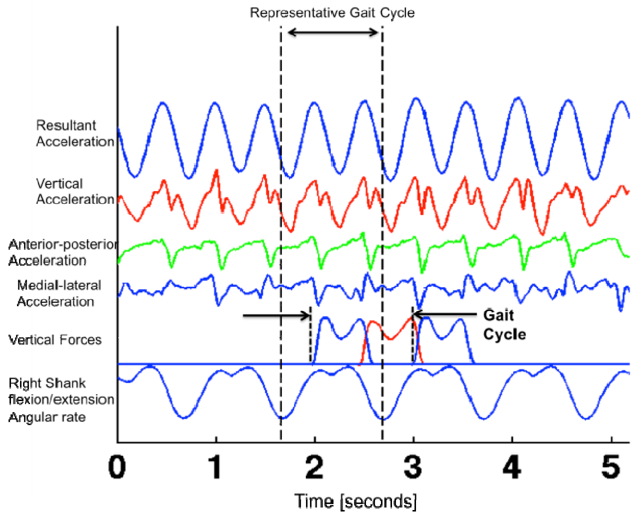

Figure 1: Two consecutive time epochs when right shank attains peak angular velocities were chosen during walking as input gait pattern data mimicking gait cycle and was defined as Representative Gait Cycle. The R-GC data from IMU situated at trunk was truncated for extraction of features values to SVM.

REFERENCES

1. Vapnik VN. *IEEE Trans Neural Netw*, **10**, 988-999, 1999.
2. Hodges SJ, et al. *J Strength Cond Res*, **25**, 3107-3017, Nov 2011.
3. Soangra R, et al. *Ann Biomed Eng*, Dec 5, 2012.

Table 1: Three feature sets were used as inputs to SVM. 1) General features, 2) Selected features and 3) Complete concatenated waveform.

	General Features	**Domain knowledge based Selected Features**	**Complete Concatenated Waveform**
Data input for SVM	-Accelerometer and gyroscope data in all 3 directions of normalized representative gait cycle	-Accelerometer and gyroscope data in all 3 directions of normalized representative gait cycle - Resultant acceleration - Resultant Jerk	-Concatenated input of normalized representative gait cycle
	i) Mean ii) Standard deviation iii) Maximum iv) Minimum v) Mean Absolute Value $\bar{x} = \frac{1}{N}\sum_{k=1}^{N}\lvert x_k\rvert$	Resultant Acceleration features i) Skewness (temporal shift) ii) Energy iii) Dominant frequency iv) Maximum acceleration v) Minimum Acceleration Range of acceleration	--No Feature--
	i) Skewness ii) Kurtosis iii) Energy iv) Number of Slope sign changes v) Number of zero crossings	Resultant Jerk features i) Skewness (temporal shift) ii) Mean Jerk at heel contact iii) Absolute Maximum Jerk iv) Absolute Minimum Jerk	
	xi) Length of waveform xii) Dominant Frequency using low-pass filter and FFT	v) Range of Jerk Produced abs(max-min) vi) Jerk Cost $JC = \int_0^T \lvert\frac{d^3r}{dt^3}\rvert^2 dt$	

Table 2: Intra-subject ankle fatigue classification using IMU derived features. Accuracy, sensitivity, specificity and AUC (area under the Receiver operating curve) are tabulated for three kinds of feature selections methods and three kernels.

		Ankle Fatigue		
		Linear	Polynomial	RBF
General Features	Accuracy	97	92	96
	Sensitivity	97.78	93.33	95.56
	Specificity	95.56	91.11	95.56
	AUC	1	1	1
Domain knowledge based Selected Features	Accuracy	98	90	97
	Sensitivity	100	91.11	100
	Specificity	95.56	88.89	93.33
	AUC	1	0.96	0.96
Normalized complete concatenated waveform signals	Accuracy	99	83	98
	Sensitivity	100	86.67	100
	Specificity	97.78	80	95.56
	AUC	1	1	1