3-2014

Classifying Lower Extremity Muscle Fatigue During Walking Using Machine Learning and Inertial Sensors

Jian Zhang
Virginia Tech

Thurmon Lockhart
Virginia Tech

Rahul Soangra
Chapman University, soangra@chapman.edu

Recommended Citation

Zhang J, Lockhart TE, Soangra R. Classifying lower extremity muscle fatigue during walking using machine learning and inertial sensors. *Ann Biomed Eng.* 2014;42(3):600-612. doi: 10.1007/s10439-013-0917-0

HHS Public Access

Author manuscript

Ann Biomed Eng. Author manuscript; available in PMC 2015 March 01.

Published in final edited form as:

Ann Biomed Eng. 2014 March ; 42(3): 600–612. doi:10.1007/s10439-013-0917-0.

Classifying Lower Extremity Muscle Fatigue during Walking using Machine Learning and Inertial Sensors

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

[1]Industrial & Systems Engineering, 557 Whittemore Hall, Virginia Tech, Blacksburg, VA 24061

[2]School of Biomedical Engineering and Sciences, Virginia Tech, Wake Forest University, Blacksburg, VA 24061

Abstract

Fatigue in lower extremity musculature is associated with decline in postural stability, motor performance and alters normal walking patterns in human subjects. Automated recognition of lower extremity muscle fatigue condition may be advantageous in early detection of fall and injury risks. Supervised machine learning methods such as Support Vector Machines (SVM) have been previously used for classifying healthy and pathological gait patterns and also for separating old and young gait patterns. In this study we explore the classification potential of SVM in recognition of gait patterns utilizing an inertial measurement unit associated with lower extremity muscular fatigue. Both kinematic and kinetic gait patterns of 17 participants (29±11 years) were recorded and analyzed in normal and fatigued state of walking. Lower extremities were fatigued by performance of a squatting exercise until the participants reached 60% of their baseline maximal voluntary exertion level. Feature selection methods were used to classify fatigue and no-fatigue conditions based on temporal and frequency information of the signals. Additionally, influences of three different kernel schemes (i.e., linear, polynomial, and radial basis function) were investigated for SVM classification. The results indicated that lower extremity muscle fatigue condition influenced gait and loading responses. In terms of the SVM classification results, an accuracy of 96% was reached in distinguishing the two gait patterns (fatigue and no-fatigue) within the same subject using the kinematic, time and frequency domain features. It is also found that linear kernel and RBF kernel were equally good to identify intra-individual fatigue characteristics. These results suggest that intra-subject fatigue classification using gait patterns from an inertial sensor holds considerable potential in identifying “at-risk” gait due to muscle fatigue.

Keywords

Fatigue; gait; Falls; machine learning; support vector machines; jerk cost

Corresponding Author: Thurmon E. Lockhart, lockhart@vt.edu.

Introduction

Localized muscle fatigue is a potential risk factor for slip-induced falls [1] as muscle fatigue adversely affects proprioception [2–4], movement coordination and muscle reaction times [5] leading to postural instability [6] and gait alterations [1, 7]. As such, identifying "at risk" gait patterns associated with fatigue may help in assessment of fatigue related fall risks in various environments (especially in the working environments). In this study, we explore the classification potential of Support Vector Machines (SVMs) in recognizing gait patterns associated with lower extremity muscle fatigue utilizing an inertial measurement unit (IMU) [8].

Numerous classification algorithms already exist to provide human motion classification and associated movement patterns. Najafi et. al. used gyroscope data and wavelet method to analyze the "sit-to-stand" transition in relation to the fall risk [9]. Lee et al. proposed linear discriminant analysis method to classify external load conditions during walking [10]. Begg et. al. used the SVM classifier to analyze the minimum foot clearance owing to aging [11]. The SVM is considered a powerful technique for general data classification and has been widely used to classify human motion patterns with good results [12–15]. The advantage of SVM algorithm is that it can generate a classification result with limited data sets by minimizing both structural and empirical risks [16]. 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. Furthermore, existing analysis is mainly based on motion capture systems and force plate measurements. While these systems are highly accurate, they do not allow continuous monitoring outside laboratory environments [55]. Additionally, the high commercial cost and complexity of data analysis in such motion capture systems restrict their use to research environments and trained personnel only.

In the current study, we aim to monitor kinematics of walking in unconstrained environments using an IMU situated at the sternum during fatigue and no-fatigue walking conditions. IMU's may help in assessment of fall risk induced by fatigue and this mobile system may help monitoring people unobtrusively in outside environments (e.g., firefighters and construction workers, etc.). Additionally, feature selection methods as well as influences of different kernel schemes on classification accuracies were investigated. We hypothesize that lower extremity muscle fatigue will influence walking behavior and these subtle changes in gait can be classified by supervised machine learning techniques such as support vector machines.

Materials and Methods

Participants

Seventeen healthy young adults (9 males and 8 females) participated in this study. The participants mean age was 29±11 years, height was in the range of 174±10 cm, and weight was 73±12 kg. All participants were healthy, independent and non-sedentary and, were formally screened for major musculoskeletal, cardiovascular, and neurological disorders by a research coordinator during initial participant contact. Exclusion criteria of this study were factors that could interfere with gait, such as medication use, presence of neuromuscular disease and, balance and vision disorders. Informed consent was approved by the Institutional Review Board (IRB) of Virginia Tech and was signed by all participants prior to the study.

Experimental Procedure

Participants were instructed not to perform any strenuous exercise 48 hours prior to the experiment. All experiments were conducted between 11:00 AM and 4:00 PM, and this was conducted to control the circadian effects of fatigue. Walking trials were conducted both prior and after the fatigue inducement. All walking trials were conducted on a linear walkway (15.5 × 1.5 m) embedded with two force plates (BERTEC #K80102, Type 45550-08, Bertec Corporation, Columbus, OH 43212, USA) in the middle of the walkway. A six-camera ProReflex system (Qualysis) was used to collect three-dimensional movement data of participants using passive infra-red markers. A total of 5 reflective markers were attached on heels and toes of both lower limbs, and one at sacrum of the participants. Two IMU's were affixed on the participants, one at right shank (to normalize the gait cycle) and the other at the sternum level using velcro straps and surgical tapes (Figure 1).

All non-fatigue walking trials were preceded by acclimatization in laboratory environment and warm-up for about 10 minutes (walking back and forth on the laboratory track). Timeline of testing procedure is illustrated in Figure 2.

Non-fatigue Walking Trials

Participants were instructed to walk at their self-preferred pace on the walking track and gait characteristics were assessed in the middle portion (5 m) of this walkway. Infrared markers on both feet were used to determine step length, step width, heel contact velocity and single stance time. Step length (SL) refers to the linear distance in the direction of progression between successive points of foot-to-floor contact of the first foot and contralateral foot. The step length is calculated from the difference between consecutive positions of the heel contacting the floor [17]. The step width is the distance between the rear end of the right and left heel centerlines along the mediolateral axis of foot. Heel contact velocity is the instantaneous horizontal heel velocity at heel contact is calculated utilizing heel velocities in the horizontal direction at the foot displacement of 1/60 s before and after the heel contact phase of the gait cycle [17]. Single stance time refers to the time person is standing on one foot [18]. And it is one of the most significant gait parameters [19].

Reflective marker affixed on the sacrum is used to determine walking velocity. Heel contact and toe-off time events were confirmed using ground reaction forces measured (sampling frequency 1200Hz) from the forceplates positioned across the center area of the walkway. Ground reaction force measurement was reviewed in every trial for ascertaining foot placement in the desired sequence (i.e., left-right heel contacts on the two forceplates). If the foot placement did not lie at the center of the force platform the participants were requested to repeat the trial. Five good walking trials were collected and each trial consisted of 6–7 complete gait cycles.

Fatigue Inducement

A custom built Biodex (Biodex System 3 Dynamometer, Shirley, New York, USA) attachment for the shoulders was used to assess maximum voluntary isokinetic exertions (MVE) during squatting (Figure 3). The Biodex attachment was designed to measure combined torque from the ankles, knees, hips and lower back through vertical motion/force exerted via shoulders. Although MVEs were performed using the shoulder attachment with a dynamometer during squat protocol, fatigue was induced by holding 5% of their body weight in front of themselves by both hands while squatting repeatedly at 22 repetitions per minute. An exercise set was set for 5 minutes and was followed by measurement of three MVEs using dynamometer. Experimenters did not instruct participants to take break between the exercise sets, but it was kept on participant's choice to start their next new exercise set as soon as they felt they were ready for it. The exercise sets continued until the participants reached 60% of their baseline MVE; this was categorized as fatigued state (time taken by participants was 52±7 minutes to reach this state).

Fatigue Walking Trials

After inducement of fatigue as determined by degradation in MVEs, locations of all five infrared markers were re-checked. Participants did not warm-up after isotonic fatiguing exercises but were asked to walk again on the walking track at their own preferred pace. All gait characteristics were derived similar to that mentioned in non-fatigue walking section and five good walking trials were collected. The complete experiment lasted for 3–4 hours.

Instrumentation

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 [20, 21]. The data acquisition was carried out using a Bluetooth adapter and laptop through a custom built program in LabView (LabView 2009, National Instruments Corporation, Austin, TX). Data was acquired with sampling frequency of 120 Hz. This frequency is largely sufficient for human movement analysis in daily activities, which occurs, in low bandwidth [0.8–5Hz] [22]. The data was processed using custom software written in MATLAB (MATLAB version 6.5.1, 2003, computer software, The MathWorks Inc., Natick, Massachusetts) and libSVM toolbox [23]. The processor of laptop used for analysis was 2.2 GHz Intel Core i7.

Statistical Data Analysis

A repeated-measure design was used to test changes within-subject in gait parameters from normal walking and post fatigue walking trials. A paired sample t-test was used to test the gait parameters obtained using camera system and forceplates. Gait parameters such as step length, step width, heel contact velocity, and single stance time were computed for all five trials around the two forceplates [24].

Input Data to the SVM Classifier

Kinematic data from the IMU located at the sternum during walking (i.e., representative gait cycle) was used as the SVM classifier input. *Representative Gait Cycle* (RGC) was defined as the period between one-foot contact to same foot contact again representing a stride duration, which was determined by the angular velocity profiles of the shank IMU. A perfect representative gait cycle signal between two easily identifiable events of the same foot was chosen for the analysis (Figure 4). RGC started at peak right shank angular velocity and terminated at consecutive peak right shank angular velocity. IMU signals from the sternum were truncated between the RGC and normalized from 0% (beginning of RGC) to 100% (end of RGC).

Training and Testing Sets

For the classification, both training and testing data sets consisted of fatigue and no fatigue RGC data. Each normal and fatigue walking trial consisted of 6–7 gait cycles, of which two middle RGCs data were extracted from each walking trial. In total, twenty RGCs were extracted: ten RGCs were extracted from five normal walking trials and the other ten RGCs from five fatigue walking trials. In both intra-subject and inter-subject classifications, training set was kept 70% of the total number of sets whereas the remaining 30% was kept for testing.

Intra-subject classification—Training set consisted of 14 RGC data sets, 7 from each walking condition (fatigue/no-fatigue). The remaining 6 RGC data sets, 3 from each walking condition were used as testing sets in intra-subject classification.

Inter-subject classification—Inter-subject fatigue/no-fatigue classification was performed using training sets of 238 RGCs and testing sets of 102 RGC data sets.

Feature Selection Methods

General Features—The general features were chosen to include all possible spatial and temporal information from the signals. Based on the criterion of minimizing computational complexity and maximizing the class discrimination, several key features have been previously proposed for SVM classification [25]. All features in this study have been extracted from raw signals.

Mean Absolute Value: The mean absolute value of the original signal, x, $\bar{}$in order to estimate signal information in time domain:

$$\overline{x}=\frac{1}{N}\sum_{k=1}^{N}|x_k| \quad (1)$$

where x_k is the k_{th} sampled point and N represents the total sampled number over the entire signal.

Zero Crossings: Zero crossing is defined as the number of times the waveform crosses zero, in order to reflect signal information in frequency domain.

Slope Sign Changes: It is the number of times the slope of the waveform changes sign, which reflects frequency content of the signal.

Length of Waveform: It represents the cumulative curve length over the entire signal, in order to provide information about the waveform complexity.

Dominant Frequency: RGC signal was filtered using Butterworth low-pass filter of 4th order with cut-off frequency of 6 Hz. Fast Fourier Transformation (FFT) was carried out on the filtered signal and the dominant frequency was defined as the frequency with the highest magnitude.

Other general features included mean, standard deviation, maximum, minimum, skewness, kurtosis, and energy of RGC signal segments. All of these features would give a measure of waveform amplitude, frequency, and duration within a single parameter. Table 1 elaborates general features used in this study.

Selected Features—In total, 11 kinematic features were selected from the resultant walking acceleration and jerk. Resultant acceleration was calculated from the raw accelerometer data:

$$R=\sqrt{A_x^2+A_y^2+A_z^2} \quad (2)$$

where A_x, A_y, A_z are accelerations sensed by triaxial accelerometer situated on trunk in a period elapsed for one RGC. Jerk is computed as a derivative of resultant acceleration. Resultant acceleration and jerk of the trunk segment and their derived features such as mean, maximum, minimum, range, energy and dominant frequency while walking are important as they provide complete kinematics of the trunk. Helbostad and his colleagues have reported significant increase in trunk acceleration due to physical fatigue [7]. Skewness of resultant accelerations and jerk provides information of the temporal shift of peak accelerations and jerk in RGC derived signals. Jerk cost, as described by the area under squared jerk curve is an important measure to estimate the energy economy of walking.

$$JC=\int_0^T\left|\frac{d^3r}{dt^3}\right|^2dt \quad (3)$$

During walking, minimizing jerk and minimizing energy are believed to be complementary performance criteria [26, 27]. Figure 4 illustrates resultant acceleration profiles for a complete RGC. We have performed the classification with possible kinematic features, which could bring significant changes due to fatigue (Table 1).

Input Data Processing

Preprocessing of features is usually required before using the SVM classifier to maximize the classification accuracy. The input features derived from RGC signals were normalized, and the dimension of the feature space was reduced using principal component analysis.

A) Normalizing Input Data—All features values were normalized by combining training and testing feature space and dividing all of them by the maximum value of that particular feature. In this kind of scaling the input data was kept in range between 0 and 1, and where 1 was the maximum value of the feature.

B) Dimension Reduction of Feature Space—Principle Component Analysis (PCA) [28] 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.

Kernel Schemes—A kernel is a function that transforms the input data to a high-dimensional space where classification is possible. Kernel functions can be linear or nonlinear. Kernel selection plays an important role in acquiring high accuracy from SVM classification. A good selected kernel may minimize generalization error, and increase classification accuracy. The linear kernel function is the simplest kernel function and works well when there are many features in the training data. Radial Basis Function (RBF) kernel is usually the first reasonable choice as it can nonlinearly map data into higher dimensional space. Polynomial kernels are non-stationary kernels and are well suited for normalized training data.

Cross-validation—Cross-validation is a standard technique usually adopted for adjusting hyper-parameters to improve the quality of its estimates in SVM model. A five-fold cross-validation scheme was adopted to evaluate the generalizability of the SVM classifier [13, 29]. In cross-validation procedure, the training data set is uniformly divided into five subsets with one used for testing and the other four used for training and constructing the SVM decision surface. This process is continued until all subsets are used as the testing sample.

Performance Assessment of SVM Classifier—All SVM models were trained over the range of cost parameter, C (2^{-10} to 2^{10}) using linear, polynomial and radial basis function kernel. The cost parameter C controls the tradeoff between training error and margins. The criterions used to assess the classification performance of SVM classifier were:

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \times 100\% \quad (5)$$

$$Sensitivity = \frac{TP}{TP+FN} \times 100\% \quad (6)$$

$$Specificity = \frac{TN}{TN+FP} \times 100\% \quad (7)$$

where TP represents the number of true positive, SVM identified a normal no-fatigued gait that was labeled as no-fatigue; TN is the number of true negatives, identified fatigued gait data that was labeled as fatigue; FP is the number of false positives, and FN is the number of false negatives, false fatigue identification. While accuracy indicates overall detection accuracy; sensitivity is defined as the ability of the SVM classifier to accurately recognize no-fatigue condition; and specificity would indicate the SVM classifier's ability to avoid false detection. Schematic diagram of SVM classification algorithm is illustrated in Figure 5.

Furthermore, Receiver Operating Characteristic (ROC) curve was also used to evaluate SVM classifier's performance. ROC analysis is generally utilized to select optimal models and to quantify the accuracy of diagnostic tests. Besides, the Area Under the ROC Curve (AUC), which is a representation of the classification performance, was utilized to assess the effectiveness of SVM classifier. Further, tests were also conducted to evaluate performance of the SVM classifier in three different kernel functions: linear, polynomial and radial basis function (RBF) kernels.

Results

Gait parameters were extracted using forceplate and motion capture system as shown in Table 2. No significant differences were found for the step length of the participants due to inducement of fatigue. However, it was seen that participants adopted wider base of support (12% wider) in post fatigue walking trials. Although no statistical significant difference was observed in walking velocity, heel contact velocity was significantly increased ($p=0.01$) in post-fatigue walking trials.

The machine learning classification results demonstrated high intra-individual classification rates across all three types of kernel (i.e., linear, polynomial and RBF kernel). We found that linear (accuracy 97%) and RBF (accuracy 96%) kernels performed equally well in intra-individual fatigue/no-fatigue classifications (Table 3). And polynomial kernel had the lowest classification accuracy (about 88%) amongst all three different types of kernels.

Table 4 shows mean success rates of SVM classifier for inter-subject fatigue classification. SVM achieved about 90% inter-subject fatigue classification accuracies with general features for identifying fatigue among participants. Selected features from the trunk kinematics could achieve a good accuracy of 88%. Additionally, these selected set of features were analyzed statistically for both fatigue and no-fatigue conditions.

We found that features of resultant acceleration and jerk such as maximum; minimum, range, skewness, and energy along with jerk cost were significantly different for post-fatigue walking as reported in Table 5.

Computation time for linear kernel was 70.85 seconds, polynomial kernel required 15.18 seconds and RBF kernel required 16.59 seconds for classification. The inter-subject fatigue classification results from three different kernels are shown in Figure 6. Linear kernel defines a linear boundary to achieve classification (Figure 6a). Polynomial kernel utilizes polynomials of the original input data to classify post-fatigue walking and no-fatigue walking (Figure 6b). It belongs to nonlinear classification, and has more complexity and better performance when compared to linear kernel. Radial basis function kernel is the most popular kernel function, and the two curves running through support vectors are the nonlinear counterparts of the convex hulls (Figure 6c).

Discussion

In this study we explored the classification potential of SVM in recognition of gait patterns utilizing an inertial measurement unit (IMU) associated with lower extremity muscular fatigue. Limited information exist in understanding the impact of muscle fatigue on dynamic postural control during walking that may be amendable to classification schemes. Our results indicate that fatigue effects are evident in individuals' gait patterns and loading responses (as measured by an extracted feature - jerk costs). Additionally, these changes although subtle, can provide helpful information for SVM to classify the status of lower extremity muscle fatigue.

Fatiguing of the muscles around a joint may have inhibited the joint's neuromuscular feedback and synergism between joint proprioception leading to instability and gait changes [30–38]. The current results suggest that single stance duration is decreased in post-fatigue walking trials which are similar to previous findings [39]. During stance phase of the gait cycle, proprioceptive input from extensor muscles and mechanoreceptors in the sole of the foot provide the loading information [40] to the central nervous system. Thus, the reduced stance duration decreases foot-loading information through afferent sensory and proprioceptive mechanoreceptors, such as Golgi-tendon units, muscle spindles, and joint receptors, and may have adversely influenced motor control of the lower extremity during walking. Additionally, fatigue inducement increased step width [8], which may be associated with modulation of self-selected pace and loss of proprioception due to fatigue [41], or due to change in motor control schema with adoption of other compensatory strategy to increase stability. Furthermore, inducement of fatigue also increased heel contact velocity (HCV) in post-fatigue walking trials [3]. Considering HCV is a kinematic gait parameter that can drastically alter the friction demand (by change in required coefficient of friction) [51] and influence the likelihood of slip-induced falls [1, 42, 43], fatigue inducement in lower extremity may ultimately increase slip-induced fall risks. Hence, our findings support the previous studies by Helbostad et. al. [7] and Johnston et. al. [30], suggesting that lower extremity fatigue impairs gait performance and locomotor control.

Gait adaptations associated with lower extremity muscle fatigue, as described above, may influence the energetics of walking and these changes in energy costs associated with fatigued state may be utilized to classify fatigue/no-fatigue gait conditions. Assuming, walker's body mass to be a point mass and, a rigid strut connecting it to the point of ground contact. This point mass reaches the highest point at the middle of the stance phase [44–46]. The trajectory of whole body center-of-mass (COM) follows a sinusoidal path along vertical direction [44–47], which may have been influenced due to fatigue. Similarly in walking, accelerometer located at the trunk allowed the measurement of mechanical work done during walking (i.e., inducement of fatigue and its associated relationship to economy during walking as assessed by the jerk cost). Energy is defined as the external work done by muscles to maintain locomotion and is highly correlated with vertical displacement of COM. An approach to minimize vertical movements of the COM (at trunk level) was detailed by

Inman and his colleagues [48], in which they identified several mechanisms involved in flattening the trajectory of the COM [48, 49], including sagittal plane knee flexion and extension during stance phase. However, with fatigue, flattening of the trajectory of the COM may not be efficient due to the kinematics of lower extremity joints. For example, Kellis and Liassou found that ankle muscle fatigue decreased ankle dorsiflexion, while knee fatigue increased knee flexion at initial heel contact [50]. In addition, they reported increased hip extension following knee fatigue and increased plantar-flexion following ankle muscle fatigue, resulting in higher vertical movements in post-fatigue walking than that of a no-fatigue walking condition.

Hreljac and Martin concluded in their study that minimum jerk movements should also minimize energy consumption during walking [27]. When lower extremity muscle fatigue was induced, high abruptness in the trunk acceleration (Jerk) was noticed [51]. Fatiguing of the muscles in lower extremity joints may influence the joint's neuromuscular feedback and synergism between joint proprioception and muscular function leading to instability [30–38] and stiffness [1, 52]. However, constant muscular stiffness has to be maintained to minimize jerk during repetitive, skilled movements [53]. It is seen that jerk at heel contact increased in magnitude by 2.3 folds and jerk cost increased by 2.8 folds in post-fatigue walking. Higher resultant accelerations (two folds higher range of acceleration) as well as higher signal energy magnitudes (5 folds higher signal energy) in post-fatigue walking trials were observed in our study. In essence, it appears that in post-fatigue walking trials, the total energy at the sternum level goes through large fluctuations during stance and the elastic energy storage is reduced; thus, resulting in higher energy dissipation through fluctuations at the trunk level (similar to catching a baseball with fully-extended elbow with greater impact (fatigued) vs. flexed elbow with less impact (non-fatigued)). It appears that SVM can map this nonlinear inter-feature relationship using the kinematics of the trunk for better discrimination of fatigue and no-fatigue states.

Previous researchers have adopted various gait feature extraction methods for SVM classification. Begg and coworkers differentiated elderly and young gait patterns using general features on minimum foot clearance data [29]. In another study, they selected kinetic and kinematic gait features for classification [31]. Whereas Eskoifer et. al. adopted concatenated waveforms from infrared markers to classify young and elderly gait [72]. Results of our investigation (Table 3 and Table 4) indicate that features extraction methods influenced classification accuracy. In inter-individual and intra-individual fatigue classification, general feature input performed with higher classification accuracy followed by selected feature input. In essence, general features exhibited superior classification accuracy and had important gait information to classify fatigue, on the contrary, the selected feature extraction method lacked peculiar information relevant to achieving higher classification results.

Three different types of kernels were employed in SVM classifier: linear, polynomial, and RBF. Both linear and RBF kernels performed well in intra-individual fatigue/no-fatigue classifications, which complied with Lee and Grimson's report [54], showing that linear kernel performs better than polynomial kernel in SVM gait recognition. However, for inter-individual classification, RBF performed better than the other two kernels. Considering the computational cost, RBF and polynomial kernels need less time compared to linear kernel in the same conditions. As such, RBF kernel is the most promising kernel function in the fatigue classification schemes, and it may also provide better applicability to real time system implementation.

Limitations

Conclusions based on this study should be considered in context of the limitations. Due to limited number of testing and training data sets, a separate cross-validation set was not employed for generalization of regularization parameters. An IMU was placed at the sternum, which could only approximate kinematics of trunk center-of-mass, but does not accurately quantify its kinematics as this placement position may miss smaller nuances associated with fatigued data. Thus, the results of this study should be limited to kinematics of the sternum placement of participants and not to kinematics of trunk COM. It is also quite possible that during our intense fatiguing protocol, squatting exercises might have lead to some extent of anterior knee pain in few subjects, which would have added to another dimension in to altered gait (pain avoidance), beyond the altered characteristics of simple muscle fatigue. Another limitation of this study is that no feature selection method was used to extract optimal set of features. In addition, order effects are an inevitable limitation in all fatigue experiments. Fatigue level may change from day-to-day basis in humans and it also follows circadian rhythm and thus time of experiment may influence fatigue levels.

Conclusion

Inertial measurement units can assist in identification of localized muscle fatigue. Intra-subject fatigue classification results in this study ranged from 93–98%, thus body worn sensors can potentially open doors for personalized monitoring on a regular basis to identify “at-risk” gait. SVMs are powerful machine learning tools applicable to the identification of post fatigue gait patterns by using a set of gait features relevant to the kinematics of the trunk during walking.

While the algorithms allow for online implementation, it is necessary to determine an optimal feature set that could automatically identify the most significant kinematic changes in gait after inducement of fatigue. Thus, we conclude that fatigue affects kinematics and gait characteristics, which can be assessed by an IMU using support vector machines.

Acknowledgements

This research was supported by the NSF (grant #CBET-0756058) and NSF-Information and Intelligent Systems (IIS) and Smart Health and Wellbeing -1065442 and 1065262. NIOSH (grant #CDC/NIOSHR01-OH009222). Additionally, supported by the NIH (L30-AG022963-04/NIH HHS/United States).

References

1. Parijat P, Lockhart TE. “Effects of lower extremity muscle fatigue on the outcomes of slip-induced falls”. Ergonomics. Dec.2008 51:1873–1884. [PubMed: 19034783]
2. Skinner HB, Wyatt MP, Hodgdon JA, Conard DW, Barrack RL. “Effect of fatigue on joint position sense of the knee”. J Orthop Res. 1986; 4:112–118. [PubMed: 3950803]

3. Hiemstra LA, Lo IK, Fowler PJ. "Effect of fatigue on knee proprioception: implications for dynamic stabilization". J Orthop Sports Phys Ther. Oct.2001 31:598–605. [PubMed: 11665747]
4. Gear WS. "Effect of different levels of localized muscle fatigue on knee position sense". Journal of Sports Science and Medicine. Dec.2011 10:725–730. [PubMed: 24149565]
5. Hakkinen K, Komi PV. "Effects of fatigue and recovery on electromyographic and isometric force- and relaxation-time characteristics of human skeletal muscle". Eur J Appl Physiol Occup Physiol. 1986; 55:588–596. [PubMed: 3780701]
6. Lin D, Nussbaum MA, Seol H, Singh NB, Madigan ML, Wojcik LA. "Acute effects of localized muscle fatigue on postural control and patterns of recovery during upright stance: influence of fatigue location and age". Eur J Appl Physiol. Jun.2009 106:425–434. [PubMed: 19306019]
7. Helbostad JL, Leirfall S, Moe-Nilssen R, Sletvold O. "Physical fatigue affects gait characteristics in older persons". Journals of Gerontology Series a-Biological Sciences and Medical Sciences. Sep. 2007 62:1010–1015.
8. Strohrmann C, Harms H, Kappeler-Setz C, Troster G. "Monitoring kinematic changes with fatigue in running using body-worn sensors". IEEE Trans Inf Technol Biomed. Sep.2012 16:983–990. [PubMed: 22677321]
9. Najafi B, Aminian K, Loew F, Blanc Y, Robert PA. "Measurement of stand-sit and sit-stand transitions using a miniature gyroscope and its application in fall risk evaluation in the elderly". IEEE Trans Biomed Eng. Aug.2002 49:843–851. [PubMed: 12148823]
10. Lee M, Roan M, Smith B, Lockhart TE. "Gait analysis to classify external load conditions using linear discriminant analysis". Hum Mov Sci. Apr.2009 28:226–235. [PubMed: 19162355]
11. Begg RK, Palaniswami M, Owen B. "Support vector machines for automated gait classification". IEEE Trans Biomed Eng. May.2005 52:828–838. [PubMed: 15887532]
12. Chapelle O, Haffner P, Vapnik VN. "Support vector machines for histogram-based image classification". IEEE Trans Neural Netw. 1999; 10:1055–1064. [PubMed: 18252608]
13. Begg R, Kamruzzaman J. "A machine learning approach for automated recognition of movement patterns using basic, kinetic and kinematic gait data". J Biomech. Mar.2005 38:401–408. [PubMed: 15652537]
14. Lau HY, Tong KY, Zhu H. "Support vector machine for classification of walking conditions of persons after stroke with dropped foot". Hum Mov Sci. Aug.2009 28:504–514. [PubMed: 19428134]
15. Levinger P, Lai DT, Begg RK, Webster KE, Feller JA. "The application of support vector machines for detecting recovery from knee replacement surgery using spatio-temporal gait parameters". Gait Posture. Jan.2009 29:91–96. [PubMed: 18752954]
16. Vapnik VN. "An overview of statistical learning theory". IEEE Trans Neural Netw. 1999; 10:988–999. [PubMed: 18252602]
17. Lockhart TE, Smith JL, Woldstad JC. "Effects of aging on the biomechanics of slips and falls". Human Factors. 2005; 47:708–729. Win. [PubMed: 16553061]
18. Judge JO, Lindsey C, Underwood M, Winsemius D. "Balance Improvements in Older Women - Effects of Exercise Training". Physical Therapy. Apr.1993 73:254–265. [PubMed: 8456144]
19. Wolfson L, Whipple R, Derby C, Judge J, King M, Amerman P, et al. "Balance and strength training in older adults: Intervention gains and Tai Chi maintenance". Journal of the American Geriatrics Society. May.1996 44:498–506. [PubMed: 8617896]
20. Soangra R, Lockhart TE, Lach J, Abdel-Rahman EM. "Effects of Hemodialysis Therapy on Sit-to-Walk Characteristics in End Stage Renal Disease Patients". Ann Biomed Eng. Dec 5.2012
21. Barth AT, Hanson MA, Powell HC Jr. Lach J. "TEMPO 3.1: A Body Area Sensor Network Platform for Continuous Movement Assessment". 2009:71–76.
22. Bouten CVC, Koekkoek KTM, Verduin M, Kodde R, Janssen JD. "A triaxial accelerometer and portable data processing unit for the assessment of daily physical activity". Ieee Transactions on Biomedical Engineering. Mar.1997 44:136–147. [PubMed: 9216127]
23. Chang C-C, Lin C-J. "Libsvm". ACM Transactions on Intelligent Systems and Technology. 2011; 2:1–27.
24. Lockhart TE, Woldstad JC, Smith JL. "Effects of age-related gait changes on the biomechanics of slips and falls". Ergonomics. Oct 10.2003 46:1136–1160. [PubMed: 12933077]

25. Hudgins B, Parker P, Scott RN. "A new strategy for multifunction myoelectric control". IEEE Trans Biomed Eng. Jan.1993 40:82–94. [PubMed: 8468080]
26. Stein RB, Oguztoreli MN, Capaday C. "What is optimized in muscular movements?". Human kinetics Pub. Inc. Champaign. 1986:131–150.
27. Hreljac A, Martin PE. "The relationship between smoothness and economy during walking". Biol Cybern. 1993; 69:213–218. [PubMed: 8373892]
28. Gorban, AN.; Kgl, B.; Wunsch, DC.; Zinovyev, A. Principal Manifolds for Data Visualization and Dimension Reduction. Incorporated: Springer Publishing Company; 2007.
29. Barton JG, Lees A. "An application of neural networks for distinguishing gait patterns on the basis of hip-knee joint angle diagrams". Gait & Posture. 1997; 5:28–33.
30. Johnston RB 3rd, Howard ME, Cawley PW, Losse GM. "Effect of lower extremity muscular fatigue on motor control performance". Med Sci Sports Exerc. Dec.1998 30:1703–1707. [PubMed: 9861603]
31. Aune AK, Nordsletten L, Skjeldal S, Madsen JE, Ekeland A. "Hamstrings and gastrocnemius co-contraction protects the anterior cruciate ligament against failure: an in vivo study in the rat". J Orthop Res. Jan.1995 13:147–150. [PubMed: 7853098]
32. Baratta R, Solomonow M, Zhou BH, Letson D, Chuinard R, D'Ambrosia R. "Muscular coactivation. The role of the antagonist musculature in maintaining knee stability". Am J Sports Med. Mar-Apr;1988 16:113–122. [PubMed: 3377094]
33. Ferrell WR Jr. Rosenberg JR, Baxendale RH, Halliday D, Wood L. "Fourier analysis of the relation between the discharge of quadriceps motor units and periodic mechanical stimulation of cat knee joint receptors". Exp Physiol. Nov.1990 75:739–750. [PubMed: 2271153]
34. Johansson H, Sjolander P, Sojka P. "A sensory role for the cruciate ligaments". Clin Orthop Relat Res. Jul.1991 :161–178. [PubMed: 2060205]
35. Kennedy JC, Alexander IJ, Hayes KC. "Nerve supply of the human knee and its functional importance". Am J Sports Med. Nov-Dec;1982 10:329–335. [PubMed: 6897495]
36. Lephart SM, Henry TJ. "Functional rehabilitation for the upper and lower extremity". Orthop Clin North Am. Jul.1995 26:579–592. [PubMed: 7609967]
37. Marshall KW, Tatton WG. "Joint receptors modulate short and long latency muscle responses in the awake cat". Exp Brain Res. 1990; 83:137–150. [PubMed: 2073935]
38. Solomonow M, Baratta R, Zhou BH, Shoji H, Bose W, Beck C, et al. "The synergistic action of the anterior cruciate ligament and thigh muscles in maintaining joint stability". Am J Sports Med. May-Jun;1987 15:207–213. [PubMed: 3618871]
39. Morris ME, Cantwell C, Vowels L, Dodd K. "Changes in gait and fatigue from morning to afternoon in people with multiple sclerosis". Journal of Neurology Neurosurgery and Psychiatry. Mar.2002 72:361–365.
40. Dietz V, Duysens J. "Significance of load receptor input during locomotion: a review". Gait Posture. Apr.2000 11:102–110. [PubMed: 10899663]
41. Smith BA, Kubo M, Ulrich BD. "Gait Parameter Adjustments for Walking on a Treadmill at Preferred, Slower, and Faster Speeds in Older Adults with Down Syndrome". Current Gerontology and Geriatrics Research. 2012; 2012:1–7.
42. Karst GM, Hageman PA, Jones TF, Bunner SH. "Reliability of foot trajectory measures within and between testing sessions". J Gerontol A Biol Sci Med Sci. Jul.1999 54:M343–M347. [PubMed: 10462165]
43. Mills PM, Barrett RS. "Swing phase mechanics of healthy young and elderly men". Hum Mov Sci. Nov.2001 20:427–446. [PubMed: 11750671]
44. Cavagna GA. "Force platforms as ergometers". J Appl Physiol. Jul.1975 39:174–179. [PubMed: 1150585]
45. Cavagna GA, Heglund NC, Taylor CR. "Mechanical work in terrestrial locomotion: two basic mechanisms for minimizing energy expenditure". Am J Physiol. Nov.1977 233:R243–R261. [PubMed: 411381]
46. Cavagna GA, Saibene FP, Margaria R. "External work in walking". J Appl Physiol. Jan.1963 18:1–9. [PubMed: 14019429]

47. Lee CR, Farley CT. “Determinants of the center of mass trajectory in human walking and running”. J Exp Biol. Nov.1998 201:2935–2944. [PubMed: 9866878]

48. Inman VT. “Human locomotion”. Can Med Assoc J. May 14.1966 94:1047–1054. [PubMed: 5942660]

49. Saunders JB, Inman VT, Eberhart HD. “The major determinants in normal and pathological gait”. J Bone Joint Surg Am. Jul.1953 35-A:543–558. [PubMed: 13069544]

50. Kellis E, Liassou C. “The effect of selective muscle fatigue on sagittal lower limb kinematics and muscle activity during level running”. J Orthop Sports Phys Ther. Mar.2009 39:210–220. [PubMed: 19252259]

51. Chappell JD, Herman DC, Knight BS, Kirkendall DT, Garrett WE, Yu B. “Effect of fatigue on knee kinetics and kinematics in stop-jump tasks”. Am J Sports Med. Jul.2005 33:1022–1029. [PubMed: 15983125]

52. Toumi H, Poumarat G, Best TM, Martin A, Fairclough J, Benjamin M. “Fatigue and muscle-tendon stiffness after stretch-shortening cycle and isometric exercise”. Appl Physiol Nutr Metab. Oct.2006 31:565–572. [PubMed: 17111011]

53. Nelson WL. “Physical principles for economies of skilled movements”. Biol Cybern. 1983; 46:135–147. [PubMed: 6838914]

54. Lee L, Grimson WEL. “Gait analysis for recognition and classification in”. Automatic Face and Gesture Recognition, 2002. Proceedings. Fifth IEEE International Conference on. 2002:148–155.

55. Liu J, Lockhart TE, Jones M, Martin T. Local Dynamic Stability Assessment of Motion impaired Elderly using Electronic Textile Pants”. IEEE Transactions in Automation Science and Engineering. 2008; 5(4):696–702.

Author Manuscript
Author Manuscript
Author Manuscript

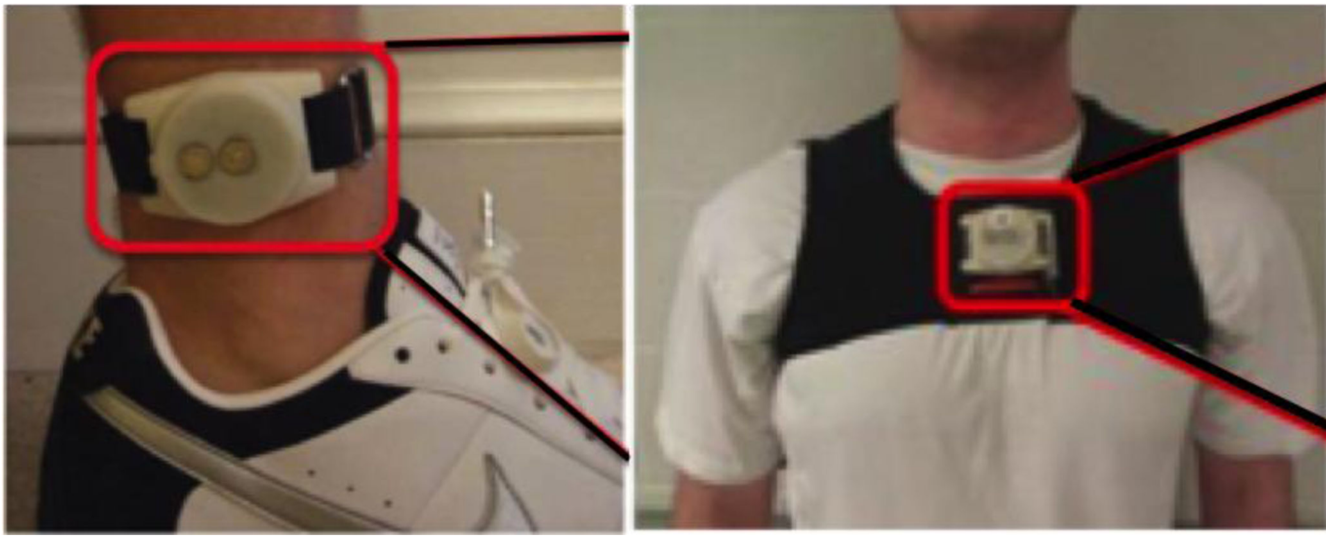

Figure 1.
Attachment of IMU sensors at (a) shank and (b) sternum level using velcro strap.

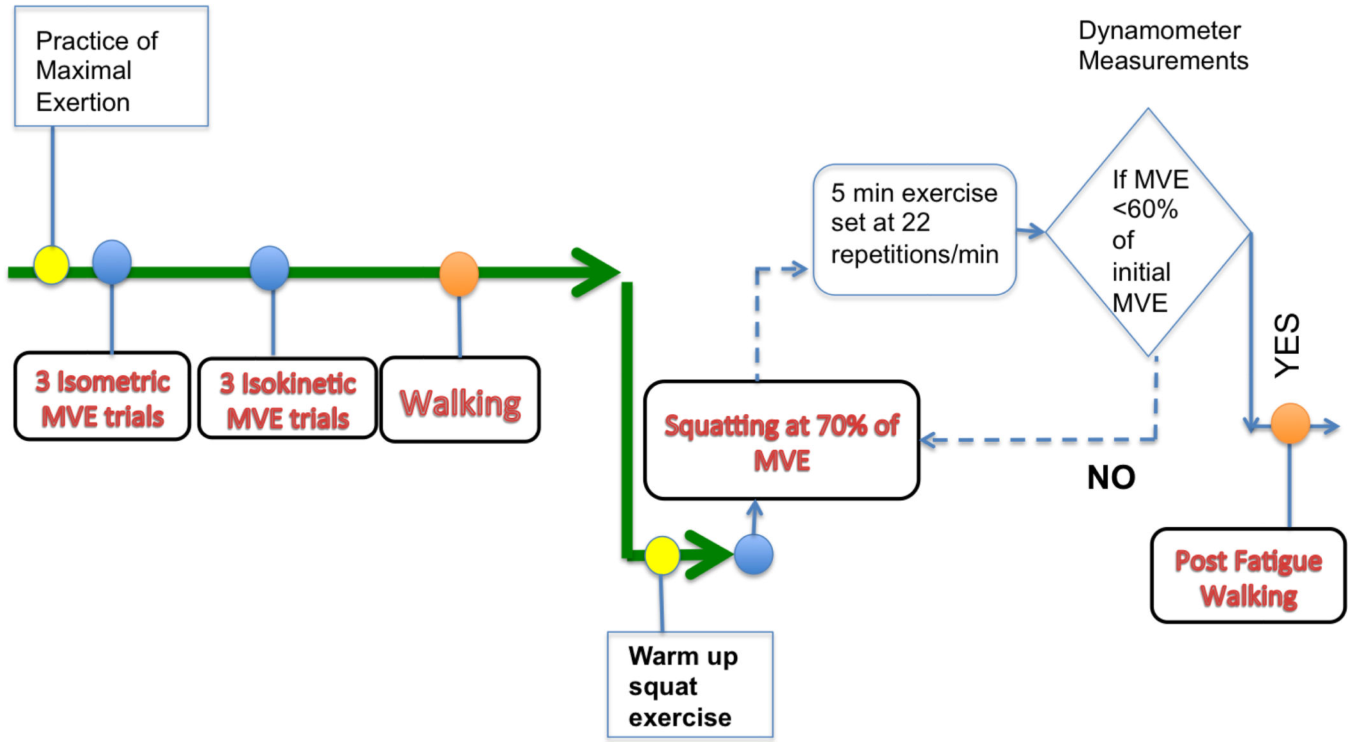

Figure 2.

Timeline of testing procedures. Practice trials were performed with the dynamometer followed by data collection for maximum voluntary torque and normal walking. Before inducing fatigue warm up exercises were conducted. Participants were considered fatigued when their isokinetic MVC was below 70% of initial isokinetic values for all three trials.

Figure 3.
Customized Biodex attachment for measurement of maximum voluntary exertions.

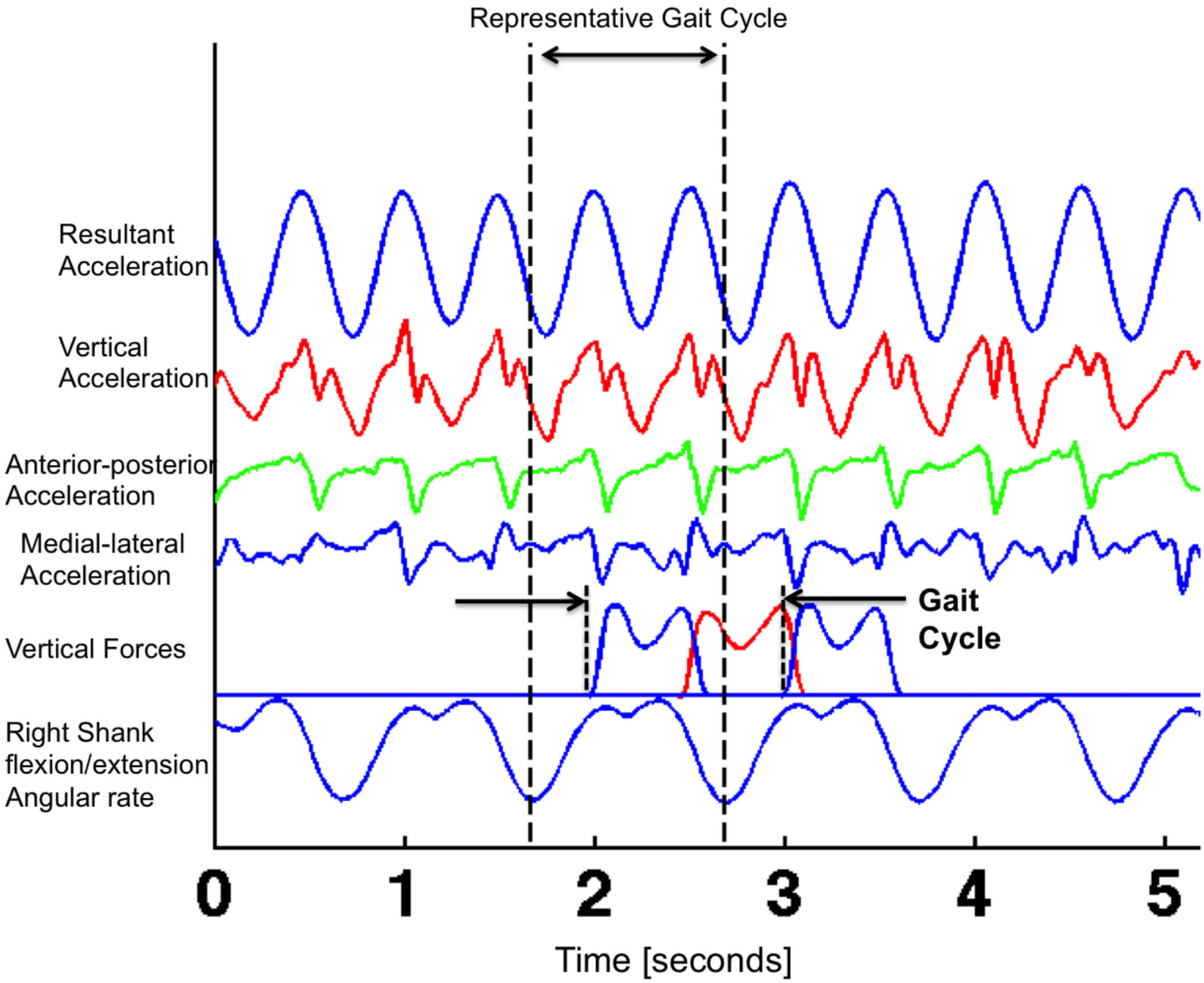

Figure 4.
Two consecutive time epochs when right shank attains peak angular velocities were chosen during walking as input gait pattern data mimicking gait cycle and was defined as Representative Gait Cycle. The R-GC data from IMU situated at trunk was truncated for extraction of features values to SVM.

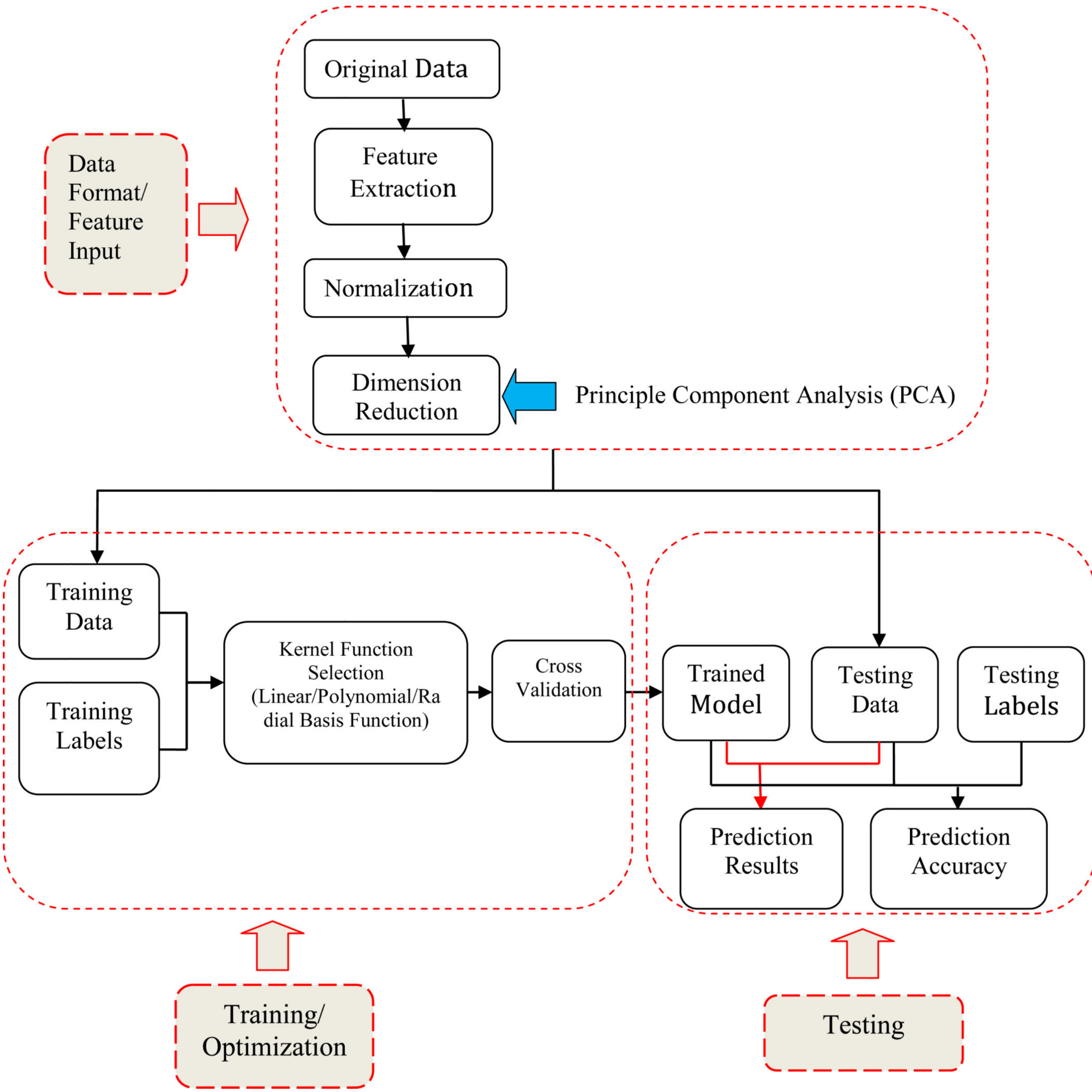

Figure 5.
Schematic diagram of procedure of SVM classification.

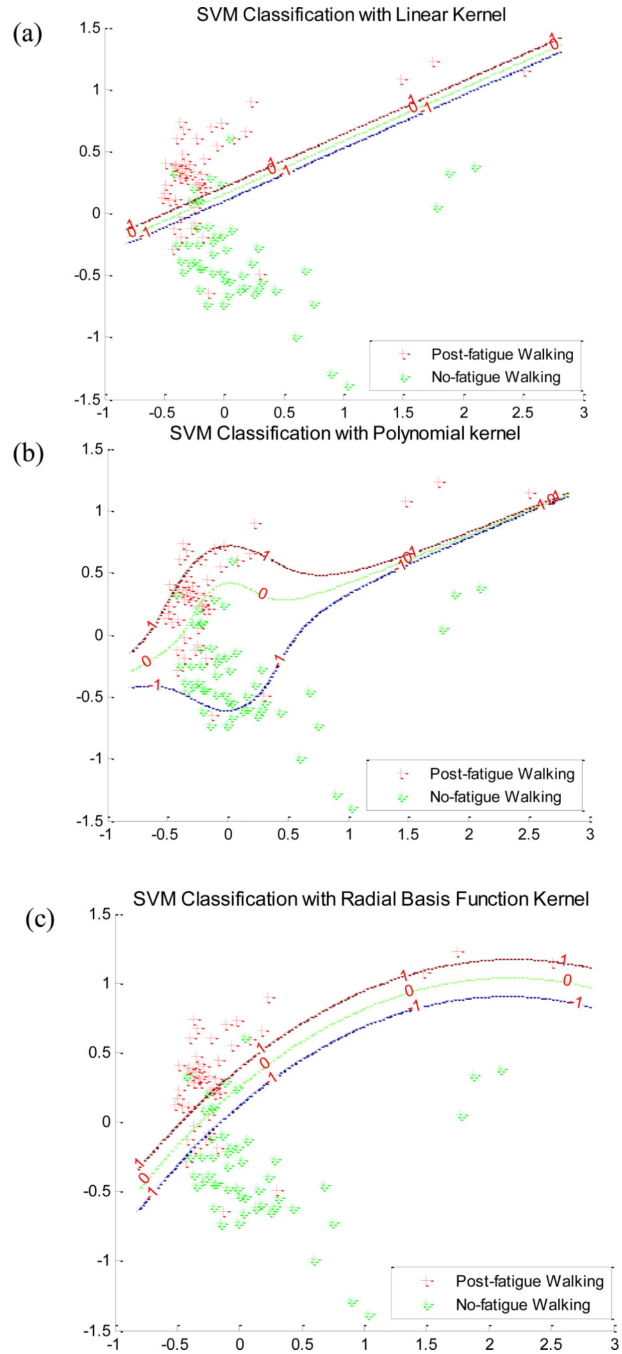

Figure 6.
Inter-subject fatigue classification results via three different kernels: (a) linear kernel; (b) polynomial kernel, and (c) radial basis function kernel.

Table 1

Three feature sets were used as inputs to SVM. 1) General features, 2) Selected features.

	General features	**Domain knowledge based selected features**
Data input for feature extraction	Accelerometer (A_x, A_y, A_z) and gyroscope (G_x, G_y, G_z) signals in all 3 directions of normalized RGC	- Resultant acceleration $(R=\sqrt{A_x^2+A_y^2+A_z^2}$ - Resultant Jerk $(J=\frac{dR}{dt})$
	• Mean • Standard deviation • Maximum • Minimum • Mean absolute value $\overline{x}=\frac{1}{N}\sum_{k=1}^{N}\lvert x_k\rvert$ • Skewness • Kurtosis • Energy • Number of slope sign changes • Number of zero crossings • Length of waveform • Dominant frequency using low-pass filter and FFT	Resultant acceleration features • Skewness (temporal shift) • Energy • Dominant frequency • Maximum acceleration • Minimum acceleration • Range of acceleration Resultant jerk features • Skewness (temporal shift) • Mean jerk at heel contact • Absolute maximum jerk • Absolute minimum jerk • Range of jerk produced abs (max-min) • Jerk cost $JC=\int_0^T\lvert\frac{d^3r}{dt^3}\rvert^2dt$

Table 2

Step length (mm), step width (mm), heel contact velocity (mm/sec), walking velocity (m/sec) and stance duration (seconds) were evaluated for no fatigue and post fatigue walking trials. The data provided is in mean ± SD for the group and paired t-test was used with alpha set at 0.05.

	No fatigue	Post fatigue	p-value
Step length (mm)	755±59	748±58	0.22
Step width (mm)	110±32	123±38	0.02*
Heel contact velocity (mm/sec)	569±110	637±122	0.01*
Walking velocity (m/sec)	1.41±0.15	1.40±0.16	0.90
Single stance time (sec)	0.68±0.04	0.66±0.04	0.005*

Table 3

Intra-subject 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.

Intra-subject classification				
		Linear	**Polynomial**	**RBF**
General Features	Accuracy	0.97	0.88	0.96
	Sensitivity	0.98	0.92	0.98
	Specificity	0.96	0.84	0.94
	AUC	0.98	0.98	0.98
Selected Features	Accuracy	0.93	0.86	0.93
	Sensitivity	0.90	0.82	0.88
	Specificity	0.96	0.90	0.98
	AUC	0.96	0.94	0.97

Table 4

Inter-subject fatigue classification using forceplate and 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.

Inter-subject classification				
		Linear	**Polynomial**	**RBF**
General Features	Accuracy	0.88	0.90	0.90
	Sensitivity	0.88	0.92	0.92
	Specificity	0.88	0.88	0.88
	AUC	0.93	0.92	0.95
Selected Features	Accuracy	0.85	0.85	0.88
	Sensitivity	0.80	0.82	0.86
	Specificity	0.90	0.88	0.90
	AUC	0.93	0.92	0.94

Table 5

Selected features from IMU were computed for no-fatigue and post fatigue walking and statistical analysis is reported.

Gait characteristics from IMU	Features	No-fatigue walking	Post-fatigue walking	p-value
Resultant acceleration	Maximum [g]	0.201	0.428	<0.0001
	Minimum [g]	0.042	0.127	<0.0001
	Range [g]	0.157	0.301	<0.0001
	Skewness	0.209	0.078	0.0333
	Energy [g^2. sec]	2.144	10.150	0.0006
	Dominant frequency [Hz]	1.494	1.558	0.1584
Jerk	Maximum [g/sec]	0.010	0.022	<0.0001
	Minimum [g/sec]	0.009	0.018	0.0003
	Range [g/sec]	0.021	0.041	<0.0001
	Skewness	0.185	0.317	0.0493
	Jerk at Heel Contact [g/sec]	0.003	0.007	<0.0001
	Jerk cost [g^2/sec]	0.007	0.022	0.0233