Abstract—Monitoring of postures and activities is used in many clinical and research applications, some of which may require highly reliable posture and activity recognition with desired accuracy well above 99% mark. This paper suggests a method for performing highly accurate recognition of postures and activities from data collected by a wearable shoe monitor (SmartShoe) through classification with rejection. Signals from pressure and acceleration sensors embedded in SmartShoe are used either as raw sensor data or after feature extraction. Support Vector Machine (SVM) and Multi-Layer Perceptron (MLP) are used to implement classification with rejection. Unreliable observations are rejected by measuring the distance from the decision boundary and eliminating those observations that reside below rejection threshold. The results show a significant improvement (from 97.3% ± 2.3% to 99.8% ± 0.1%) in the classification accuracy after the rejection, using MLP with raw sensor data and rejecting 31.6% of observations. The results also demonstrate that MLP outperformed SVM, and the classification accuracy based on raw sensor data was higher than the accuracy based on extracted features. The proposed approach will be especially beneficial in applications where high accuracy of recognition is desired while not all observations need to be assigned a class label.

Index Terms—wearable sensors, physical activity, risk of falling, gait analysis, classification algorithms, biomedical signal processing.

I. INTRODUCTION

Monitoring of posture allocations and physical activities is important in many areas of biomedical research [1]. For instance, prostate cancer has been proven to be directly related to extensive sitting [2] and obesity may be caused by insufficient physical activity (e.g. walking, standing) and prolonged car driving [3]. Higher physical activity was associated with lower risk of osteoporosis [4]. Moreover, abnormal patterns of daily activities are symptoms of many diseases. It is reported that the children with autism have weaker muscles which may result decreased daily activities [5]. The same situation exists in the post-stroke patients[6] and patients with Amyotrophic Lateral Sclerosis [7].

Some of the research and clinical applications may require very high reliability of classification of postures and activities, well in excess of 99%. For example, cadence, stance time, etc. are used as an important clinical metrics during post-stroke rehabilitation [6] or in prediction of risk of falling [8]. However, extraction of gait parameters can only be meaningful during walking. If gait assessment is performed in a fully automatic manner by first recognizing the activity (walking) and then measuring gait parameters, then any errors in activity classification (for example, recognizing fidgeting while standing as walking) will negatively impact accuracy of gait parameters measurement. Therefore, for accurate gait assessment it is critical that walking is recognized with accuracy as close to 100% as possible. However, not all episodes of walking need to be recognized as sufficient gait statistic can be accumulated over those episodes that are recognized with high reliability. With this approach, the gait assessment accuracy will be improved by eliminating outliers resulting from confusion with non-walking activities. In a way this can be compared to blood chemical analysis that does not require drawing all of the blood, but rather a small but very clean, not contaminated sample. Similarly, highly accurate recognition of standing may be necessary to accurately measure center of mass trajectory in postural balance analysis, and so on.

While many methods and devices exist for monitoring physical activities in research, clinical and consumer applications, a few if any of them offer accuracies above 99%. For example, Mathie et al. [9] detected daily physical activities by a triaxial accelerometer with overall accuracy of 94%. Bao and Intille [10] used five wearable biaxial accelerometers located on different parts of the body to recognize daily activities, and the overall accuracy rate was 84% by applying a so-called semi-naturalistic approach (an intermediate between laboratory and naturalistic monitoring). Baek et al. [11] extracted statistical features (such as mean, standard variation, and skewness) from accelerometer data to classify activities. The overall rate of correct classification was about 97.5%. Some activity monitoring devices are commercially available, such as the Intelligent Device for Energy Expenditure and Activity (IDEEA) developed by MiniSun, activPAL by PAL Technologies Ltd., and SenseWear by BodyMedia Inc. An extensive review of many published methods and devices can be found in [12].

Our group has developed a shoe-based activity monitoring system (SmartShoe) that has the advantage of being able to differentiate between weight-bearing and non-weight-bearing
activities (such as sitting vs. standing, walking vs. cycling) that present difficulties to other monitors [1]. SmartShoe resolves the issues common to other monitors by incorporating pressure and acceleration sensors in footwear. SmartShoe has been used for recognition of postures and activities in healthy [1] and post-stroke [6] individuals, accurate estimation of caloric energy expenditure [13], measurement of temporal gait parameters [14], and prediction of body weight [15]. While the overall accuracy of recognition of basic postures and activities by SmartShoe has been high and varied between 95% and 98% [1, 6], it may still be less than desired overall accuracy above 99%. Some activities, such as ascending and descending stairs, have even lower recognition accuracy (84% and 88%, respectively).

This paper suggests a method for highly accurate classification of postures and activities through classification with rejection. This method rejects the data points that are very close to the classifier’s decision boundary and therefore are deemed unreliable. For example, if there are 1,000 data points to be classified, 200 data points that are relatively close to the decision boundary may be rejected (not assigned a class label). However, the remaining 800 data points may have a 0.99 probability of being classified correctly. This technique has a sound theoretical justification [16] and has been successfully used in such applications as sleep state classification [17] and speech recognition [18]. This method can improve the accuracy of the classification significantly, especially for big sample size classifications where not every observation needs to be assigned a class label. While the method is validated with SmartShoe, it can potentially be extended to other types of activity monitors.

The rest of the paper is organized as follows: Section II presents a description of the SmartShoe and the experimental subjects, followed by signal processing, feature extraction, description of the classification with rejection, and validation. Section III shows the results obtained. Discussion and conclusion are presented in Section IV and V, respectively.

II. METHODS AND MATERIALS

A. Shoe-based monitor system (SmartShoe)

The SmartShoe contains six sensors total in each shoe as shown in Fig. 1, including five pressure sensors on the insole and one three dimensional accelerometer on the heel of the shoe. A more detailed description can be found in [1]. A single sample of data from a shoe is represented by vector \( S = \{ AAP, AML, ASI, PH, PSM, PSM, PIM, PHX \} \), where \( AAP \) is anterior–posterior acceleration, \( AML \) is medial–lateral acceleration, \( ASI \) is superior–inferior acceleration, \( PH \) is heel pressure, \( PSM \), \( PSM \), \( PIM \) are pressures from fifth, third, and first metatarsal head sensors, respectively, and \( PHX \) is pressure from the hallux sensor. Our previous study has shown a higher accuracy of classifying postures could be achieved by discarding signals from \( PSM \) and \( PSM \) [1]. Thus, those signals were discarded in the analysis from the beginning.

The pressure and acceleration signals from the SmartShoe were collected with a 400 Hz sampling frequency and down sampled to 25Hz by averaging. The resolution for the pressure sensor was 0.5% of full scale [19], and the accelerometer’s resolution was 1.0 mg [20].

B. Subjects

Nine subjects, six females and three males, were recruited to participate in the study (anthropometric characteristics are shown in Table I).

All the subjects were required to perform a variety of activities (sit, stand, walk/jog at difference pace, ascend stairs, descend stairs and cycle) while wearing SmartShoe on both feet. All subjects were healthy and informed written consent was obtained from each participant. The research protocol was approved by the Institutional Review Board (IRB) at Clarkson University, Potsdam, NY where the study was conducted.

![Fig. 1 A pair of shoes with wearable sensors, wireless transmitter, and batteries. The accelerometers on the back of the shoes can measure anterior–posterior (AAP ), medial–lateral (AML ), and superior–inferior (ASI ) axes of acceleration. Pressure sensitive insoles are equipped in the shoes. PH is heel pressure sensor, PSM, PSM, PSM are the fifth, third, and first metatarsal head sensors, respectively, and PHX is the hallux sensor.](image)

TABLE I. THE ANTHROPOMETRIC CHARACTERISTICS OF THE NINE SUBJECTS

<table>
<thead>
<tr>
<th>Subject</th>
<th>Gender</th>
<th>Weight (kg)</th>
<th>Height (inches)</th>
<th>BMI ( a )</th>
<th>Age</th>
<th>Shoe size</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>F</td>
<td>55</td>
<td>64.25</td>
<td>20.7</td>
<td>24</td>
<td>7.5</td>
</tr>
<tr>
<td>2</td>
<td>F</td>
<td>55.6</td>
<td>62.25</td>
<td>22.2</td>
<td>18</td>
<td>7</td>
</tr>
<tr>
<td>3</td>
<td>M</td>
<td>83</td>
<td>67.75</td>
<td>28.0</td>
<td>31</td>
<td>10.5</td>
</tr>
<tr>
<td>4</td>
<td>F</td>
<td>70</td>
<td>61</td>
<td>29.2</td>
<td>26</td>
<td>8.5</td>
</tr>
<tr>
<td>5</td>
<td>F</td>
<td>100.9</td>
<td>63</td>
<td>39.4</td>
<td>29</td>
<td>7.5</td>
</tr>
<tr>
<td>6</td>
<td>M</td>
<td>84</td>
<td>71</td>
<td>25.8</td>
<td>20</td>
<td>10.5</td>
</tr>
<tr>
<td>7</td>
<td>M</td>
<td>59</td>
<td>69.5</td>
<td>18.9</td>
<td>22</td>
<td>9.5</td>
</tr>
<tr>
<td>8</td>
<td>F</td>
<td>59.2</td>
<td>70</td>
<td>18.7</td>
<td>20</td>
<td>9</td>
</tr>
<tr>
<td>9</td>
<td>F</td>
<td>67.6</td>
<td>66</td>
<td>24.1</td>
<td>23</td>
<td>8.5</td>
</tr>
</tbody>
</table>

\( a \) Body Mass Index (BMI)

C. Signal processing

The signals collected from the SmartShoe sensors were divided into segments (epochs) of 2s duration that were used as an atomic time interval for posture/activity classification. Table II shows counts of all the epochs recorded for six classes of postures and activities, totaling in over 11.5 hours of data (20,890 epochs), with 3,218 epochs for sitting, 3,207 epochs for standing, 10,721 epochs for walking and jogging, 550 epochs for ascending stairs, 506 epochs for descending stairs, and 2,688 epochs for cycling. Thus, the dataset
includes several thousand observations for most of the classes and should be sufficient for reliable estimation of posterior probabilities. The time series of data from both shoes were combined as \( f_i = [S_L, S_R] \), \( i = 1, \ldots, M \), where \( S_L, S_R \) were the data samples from the left and right shoe, respectively, and \( M \) was the length of time series.

To convert sensor signals from the ADC units (in this case 0 to 4,095, 12bit ADC) to a range of \([0,1]\), a “min-max” normalization procedure was performed on the sensor data as following,

\[
x_i = \frac{(X_i - \min(F))}{(\max(F) - \min(F))},
\]

where \( X_i \) is the sensor signal for \( i-th \) epoch, \( x_i \) is normalized value of \( X_i \) and \( F \) is the entire sensor signal. After the normalization, all the elements follow \( x_i \in [0,1] \). The normalization coefficients here are defined by the sensor scale and are not subject-specific (e.g. pressure sensor readings saturated at approximately the same value for all subjects). Thus, this normalization procedure is capable of normalizing the signal in real time, if required by application. The data set after the normalization is raw sensor data set, and classifiers can be trained and validated with the raw sensor data without further processing.

**TABLE II. THE SAMPLE SIZE FOR THE SIX POSTURES**

<table>
<thead>
<tr>
<th>Posture</th>
<th>Sit</th>
<th>Stand</th>
<th>Walk / Jog</th>
<th>Ascend stairs</th>
<th>Descend stairs</th>
<th>Cycle</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>No. of epochs</td>
<td>3218</td>
<td>3207</td>
<td>10721</td>
<td>550</td>
<td>506</td>
<td>2688</td>
<td>20890</td>
</tr>
</tbody>
</table>

### D. Feature Extraction

Computing statistical features is usually helpful in classification [15, 21]. This study involved feature extraction with the goal to test if classification accuracy can be improved by using feature data over raw sensor data. The features were mean value, minimum value, standard deviation, entropy, variance, maximum value, number of mean crossings (NMC), mean absolute deviation (MAD), and the ratio between root mean square of wavelet coefficients at the anterior-posterior direction and that at the vertical direction (RAV) [22]. NMC is the count of times that the curve composed by the sample values crosses the mean value. MAD is the mean of the absolute deviations of a set of data about the data’s mean [23]. The nine features were derived from each of the six sensor signals (pressure signals from three locations and three dimensional acceleration signals), respectively. Thus, the number of computed features in 2 seconds will be 54 features (9 features per sensor signals multiplied by 6 sensor signals). Another two features, the ratio of maximum acceleration and the maximum pressure, and the pressure values at the moment of maximum acceleration, brought the total to 56 features.

### E. Support vector machine with rejection

The first tested classifier was SVM which is widely used for pattern classification [18], and was developed from the theory of Structural Risk Minimization (SRM) [24]. SVM supports classification with rejection both in binary [25] and multi-class formulations [26].

The method of classification with rejection by SVM has been proven to be an effective approach to improve classification accuracy in [17, 18, 25, 27, 28]. For a two-class SVM classifier, outputs could be modified to construct a posterior probability estimate (PPE) from the distance of an observation (in this case an epoch of sensor signals) to the decision boundary [29]. The PPEs, in turn, are used to estimate reliability of a classification and reject unreliable observations.

For the classical two-class (binary) formulation of SVM classification, the output of an SVM classifier is in the form

\[
y = \text{sign}(f(x)),
\]

\[
f(x) = \sum_{i=1}^{N_{SV}} \alpha_{ij} y_i k(x_i, x_j) + b,
\]

where \( y_i \) are the class targets, \( x_i \) are the input data points, \( N_{SV} \) is the number of support vectors, \( \alpha_{ij} \) are the Lagrange multipliers from solving quadratic optimization problem, \( k(x_i, x_j) \) is a kernel function [30], and \( b \) is the bias. RBF kernel was used here since it usually provides a better performance in the classification than other kernels [31]. In case of binary classification, PPE can be obtained from \( f(x) \) as

\[
p(x) = \frac{1}{1 + \exp\left(n \times \left| f(x) \right| \right)} = \frac{1}{1 + \exp(n \times (d_w - d_x))},
\]

where \( |f(x)| \) is the absolute value of \( f(x) \), \( \left\| \omega \right\| \) is the norm of the weight vector of the separating hyperplane, \( (d_w - d_x) \) is the distance between current input and a support vector, \( n \) is a scaling factor derived from cross-validation.

For a multi-class classification problem such as the problem at hand, several binary SVM classifiers need to be utilized. For example, one-against-one classification method trains \( k(k-1)/2 \) binary classifiers (where \( k \) is the number of classes) to solve \( k \) class classification problem. During prediction the class with most votes becomes the winner. One-against-one compares favorably with other multi-class SVM classification methods [32] and is a default choice in the libSVM package [30] that has been utilized in this study. The posterior probability for the winning class in one-against-one classification can be obtained by a variety of methods in the cases of multi-class classification [33]. LibSVM implements the following iterative algorithm for performing pairwise coupling and estimating posterior probabilities [33].

Given the input epoch \( x \) and the class label \( y \), let \( r_{ij} \) to denote the estimated pairwise class probabilities of \( \mu_{ij} = P(y = i | y = i \text{ or } j, x) \) and assume \( r_{ij} + r_{ji} = 1 \). To obtain \( r_{ij} \), an optimization problem is formulated as:

\[
\min_{P_{ij}} \sum_{i=1}^{k} \sum_{j=1}^{k} \left( r_{ij} p_i(x) - r_{ij} p_j(x) \right)^2 \text{ subject to } \sum_{i=1}^{k} p_i(x) = 1.
\]

where \( p_i(x) = P(y = i | x) \), \( i = 1, \ldots, k \). Problem (5) can be rewritten as
where \( p(x) \) is the vector of multi-class probability estimates, and

\[
Q_{ij} = \begin{cases} 
\frac{1}{n} p_i^2 & \text{if } i = j, \\
-\frac{1}{n} p_i p_j & \text{if } i \neq j.
\end{cases}
\]

A \( p(x) \) is a global minimum if and only if it satisfies the optimality condition:

\[
\begin{bmatrix} Q & e \\
e^T & 0 \end{bmatrix} p(x) = \begin{bmatrix} 0 \\
1 \end{bmatrix}
\]

where \( e \) is the \( k \times 1 \) vector of all ones, and \( \theta \) is the \( k \times 1 \) vector of all zeros. \( \alpha \) is the Lagrangian multiplier of the equality constraint \( \sum_{i=1}^{k} p_i(x) = 1 \). Here \( Qp(x) \) is the derivative of \( (6) \).

Thus, the solution to the problem \( (5) \) can be obtained by solving the linear system \( (8) \). The algorithm of an iterative method for solving \( (8) \) is given as:

1. Start with initial \( p_i(x) \geq 0 \), \( \forall i \) and \( \sum_{i=1}^{k} p_i(x) = 1 \).
2. Repeat \( (t = 1,...,k,1,...) \)

\[
p_j(x) \leftarrow \frac{1}{Q_{nn}} \left[ -\sum_{j:j \neq i} Q_{ij} p_j(x) + p^T(x) Qp(x) \right]
\]

normalize \( p(x) \) until \( (8) \) is satisfied. [33]

Once the PPEs were obtained, posture epochs were rejected (not assigned a class label) if their PPEs were below the desired threshold value \( T_{SVM} \) i.e. the \( i \)-th epoch was rejected if \( \Psi_i < T_{SVM} \).

F. Artificial neural network with rejection

The second tested classifier was MLP artificial neural network. MLP is a powerful tool in information processing system to solve pattern analysis problems or feature vectors classification [34]. A three-layer MLP implemented using Matlab’s neural network toolbox was employed to perform classification. The hidden layer of MLP contained 240 neurons for the classification of raw sensor data and 20 neurons for the classification of extracted features. Optimized Levenberg-Marquardt with adaptive momentum (OLMAM) was picked as training algorithm.

The rejection technique for MLP neural network was based on an estimate of the classification reliability [35]. The reliability evaluator is denoted as \( \Psi \). For an input epoch \( x \) only one neuron (the one associated the class that epoch \( x \) belongs to) in the output has a value of one, and all other neurons would have zero values, however, the actual output usually has all neurons with nonzero values. The most common rule of winner-takes-all [36] assigns an input epoch \( x \) to the class associated with the neuron with the highest output. In classification with rejection, if \( D_1 \) and \( D_2 \) are the highest value and the second highest value in the output, respectively, the reliability evaluator is defined as \( \Psi = D_2 - D_1 \) and it can take values between zero and the maximum network output value. Zero value is considered unreliable. Epochs are rejected if their \( \Psi \) values are below the desired threshold \( T_{MLP} \), i.e. the \( i \)-th epoch was rejected if \( \Psi_i < T_{MLP} \).

G. Validation

The Leave-One-Out (LOO) [37] validation method was used to evaluate the performance of the classifiers described in this study. The entire dataset from one subject were taken for validation and the epochs of the remaining subjects (eight subjects in this study) were used to train the classifier. The training and validation sets never shared any data from the same subject. This procedure was repeated nine times until all subjects were considered for testing. All the test results were then combined into a cumulative confusion matrix, allowing calculation of the class-specific recall (the proportion of a class instances that are correctly identified) and class-specific precision (the proportion of the predicted class cases that are correct) for each posture. The classification accuracy results across all subjects were summarized by the mean and the standard deviation of the accuracy rates from the validation. The validation procedure was performed on all combination cases, with rejection technology and without rejection technology, and with raw sensor data and extracted features.

H. Testing on the significance of the improvement

Statistical significance of the changes before and after the rejection in the mean classification accuracy was tested by a non-parametric Wilcoxon signed rank test (Wilcoxon T test) [38]. The choice of the non-parametric statistical test was defined by the skewness of the accuracy data toward 100%.

III. RESULTS

Changing rejection threshold changes the number of rejected epochs and classification accuracy. Fig. 2 addresses the cost of omitted epochs versus the classification performance. To achieve the highest classification accuracy and keep majority of the epochs, different threshold values were chosen for different cases. For SVM, the threshold values were 0.99 for raw data and 0.95 for feature data. For MLP, they are 0.90 and 0.95, respectively.

To show the improvement in recognition of all the six classes after the rejection, the results for MLP classifier operating raw sensor data are presented as a cumulative confusion matrix before and after the rejection (Table III). The percentage of the epochs remaining after rejection was 68.4%. Table IV presents the class-specific recall and precision values for the six classes when SVM and MLP were used on the raw and feature data, with and without the rejection. Table V provides a summary of the mean recognition accuracy and the standard deviation computed by LOO across all subjects. Note that both the mean accuracy and the standard deviation were improved after rejection.

IV. DISCUSSION

The results demonstrate that classification with rejection improved the accuracy of posture and activity classification both for SVM and MLP classifiers according to Table V.
The recognition accuracy across all subjects was 99.8% with standard deviation of only 0.1% (for MLP applied to raw sensor data). For SVM, best classification accuracy was 98.7% ± 1.9%. The statistical test indicates that the mean accuracy from all the testing cases were improved significantly after the rejection (p-value < 0.05).

The best recognition accuracy across all subjects was 99.8% with standard deviation of only 0.1% (for MLP applied to raw sensor data). For SVM, best classification accuracy was 99.9% with standard deviation of only 0.1% (for MLP applied to raw data). The statistical test indicates that the mean accuracy from all the testing cases were improved significantly after the rejection (p-value < 0.05).

While the absolute increase in average classification accuracy is only 2.5% (MLP with raw data) it is a step which brings the mean accuracy (99.8%) much closer toward 100% goal. A more pronounced increased is observed in the standard deviation of the accuracy (a factor of 23, from 2.3% to 0.1%) indicating that rejection greatly reduces inter-subject variability, producing classifications that are more accurate across the population. In addition, accuracy of classification for some classes improved dramatically after rejection. The most significant improvement for the SVM classifier is the class-specific recall of “Ascending stairs”. Those were most significant improvement for the SVM classifier is the class-specific recall of “Descending stairs”. For the MLP classifier, the most significant improvement is the class-specific recall of “Descending stairs”. Those were increased by 23.6% and 26.2% after the rejection, respectively. Recognition of “Ascending stairs” and “Descending stairs” is important in gait analysis where the locomotion on stairs is the focus of the research [39].

According to Fig.2, the higher the threshold value was, the smaller percentage of posture epochs left. With the threshold values up to 0.95, more than 50% of epochs were left. However, the overall accuracy is not necessarily increased with the increasing of the threshold values.
Both SVM and MLP showed higher accuracies after rejection when used with raw sensor data. For the extracted features, rejection increased the overall accuracy rates from 78.4% and 96.8% to 95.7% and 99.0% when using SVM and MLP, respectively. However, the class-specific recall of “Ascending stairs” and “Descending stairs” was reduced. Moreover, the feature-based SVM classifier confused many epochs among “Walk”, “Ascending stairs”, and “Descending stairs”. With the same set of features the MLP classifier performed much better than SVM. Among all the six postures, accuracy rates for “Sit”, “Stand”, “Walk”, and “Cycle” were all above 99%. Accuracy rates for “Ascending stairs” and “Descending stairs” were 94.8% and 88.3%, respectively. One possible explanation is that some information needed for accurate classification might be lost when the features were computed. It may be possible to find an improved feature set that would preserve such information while substantially reducing the size of the vectors presented to classifiers.

As described in Methods, MLP and SVM classifiers utilize different approaches of classification with rejection. The mean and standard deviation of the classification accuracy are comparable both for MLP and SVM with rejection, thus supporting the validity of the proposed classification methodology. In future studies, we will recruit a larger dataset in free living conditions (i.e. subjects performing activities of daily living in the community) that would allow for a more robust validation.

The results also show that MLP outperformed SVM in accuracy of classification. MLP was slightly better than SVM model for the raw data and significantly better in the feature space. This may be explained by the properties of the dataset that may be more favorable to MLP classification. Similar results of MLP outperforming SVM have been reported in a number of studies, including writer identification using Arabic script [40] and bio-activity classification [41]. However, SVM is faster than MLP in the speed of learning in this study. The elapsed time when performing SVM to train with eight subjects is 185.3 ± 7.8 seconds and 99.7 ± 3.7 seconds on the raw and feature data, respectively. The elapsed time when performing MLP on training is 1775.8 ± 24.7 seconds and 260.4 ± 98.3 seconds on the raw and feature data, respectively. For the elapsed time of testing a subject, SVM has mean values of 9.0 seconds and 0.9 seconds on the raw and feature data, respectively. MLP has mean values of 0.1 seconds and 0.04 seconds. These results suggest that SVM algorithm is faster in learning, but slower in testing compared to MLP. MLP may be used in applications that need real-time posture and activity classification. The time calculation was based on a computer with 64 bit Windows 7, Intel (R) Core (TM) i7-2600K CPU @ 3.40GHz, and 8GB RAM.

Overall, classification with rejection allowed very accurate posture and activity classification while rejecting an acceptable fraction of total observations (epochs). This methodology can potentially be extended to include more postures and activities and applied to other activity monitors. This technique would benefit many applications that do not need to assign a class label to every observation. Such applications may include automatic gait analysis for neurological diseases such as Parkinson’s or stroke, or, activity-specific analysis of risk of falling in elderly, which is the ultimate goal for which the proposed methodology was developed.

V. CONCLUSION

This paper suggests a method for classifying multiple postures and activities by using classification with rejection. High overall recognition accuracy, 99.8%± 0.1%, has been reached by using a multi-layer perceptron applied to raw sensor data, while rejecting only 31.6% of the observations. In this study, classification by a multi-layer perceptron outperformed support vector machines and classification using raw sensor data produced better results than classification using extracted features. While classification with rejection is an established theoretical technique, it remains underutilized in practice. This study shows the potential of classification with rejection for biomedical research where accuracy of the decision is important and the sample size is large. Future biomedical applications could take advantage of this approach to ensure reliable classification.

REFERENCES


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