The application of multiclass SVM to the detection of knee pathologies using kinetic data: a preliminary study

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Abstract

Knee pathologies such as patellofemoral pain syndrome (PFPS) and knee osteoarthritis (OA) can lead to pain and disability. PFPS limits mobility and potentially leads to knee osteoarthritis. A common treatment for knee OA is joint replacement surgery. In this paper, we investigated the application of multiclass Support Vector Machines (SVM) to classify gait patterns between three knee pathology groups using ground reaction force (GRF) data. Results indicate that the multiclass SVM could identify the different knee pathologies with a maximum leave one out (LOO) accuracy of 78%-88% on the testing set. When feature selection was applied, the accuracy improved to 85%-92% and accuracy on the test set improved from 37% to 62%. The SVM detected 7 and 8 GRF features related to the peak GRFs and their relative timing as being sensitive to distinguish between patients with knee replacement and both knee OA and PFPS, respectively. Only 2 features (peak anterior GRF and time to heel strike transient) were required to discriminate knee OA from PFPS group. The SVM classifier was able to effectively recognize gait parameters that were altered due to the various knee pathology conditions. This suggests that GRF information is indicative of abnormal joint loading and can be detected using the multiclass SVM.

1. INTRODUCTION

The knee joint is one of the most common sources of chronic joint pain. Knee pathologies such as patellofemoral pain syndrome (PFPS) and knee osteoarthritis (OA) can lead to pain and disability. Patients with PFPS suffer from pain in the anterior knee which may occur during functional activities such as squatting and descending stairs. PFPS limits mobility and potentially leads to knee osteoarthritis or functional disability. Knee osteoarthritis (OA) is a chronic joint disease affecting more than 10% of the Australian population aged 45-65 years and 50% of people aged 85 years and over [1]. Knee OA impacts upon activities of daily living which consequently lead to a loss of functional independence [2]. Knee replacement is a common surgical procedure used for the management of knee OA. Knee replacement provides pain relief and improves physical function and quality of life for patients who suffer from OA [3].

Altered joint loading using ground reaction forces (GRFs) has been reported in patients with knee pathologies including PFPS and knee OA [4-9]. Previous studies have demonstrated lower vertical and anterior-posterior GRFs in subjects with degenerative diseases and PFPS [7, 8, 10]. The altered GRFs therefore has been suggested as a quick screening tool to detect abnormal joint loading [10]since it provides indirect information about the internal joint loading. Identifying the different gait characteristics of patients with various knee pathologies including PFPS, knee OA and total knee replacement during walking is, therefore, important to ascertain potential biomechanical factors for assessment, treatment and prevention of the knee pathology.

In this paper, we investigated the automated recognition of subjects with the following knee pathology: PFPS, knee OA and patients after total knee replacement using the multiclass Support Vector Machine (SVM) based on vertical and anterior-posterior GRFs. SVMs are powerful nonlinear classifiers based on statistical learning theory [11] which have been successfully used in various pattern recognition problems [12]. The multiclass SVM is an extension of the binary SVM classifier with a decision rule constructed based on the outputs of a combination of individual binary SVMs. To the best of our knowledge there have been no previous reports on the application of multiclass SVM to the detection and identification of different knee pathologies. Our objective was to investigate if SVMs with GRFs variables as inputs can discriminate the different knee pathologies and to determine the subset of variables that best describe PFPS, OA and total knee replacement gait.

2. KNEE GAIT DATA

A. Subjects

The gait data consists of three groups: asymptomatic 13 patients with unilateral PFPS (with mean age, mass and height of 38.4 years ± 10.11, 70.6kg ± 18.16 and 166.3 cm ± 5.97 respectively), 5 patients with end-stage knee OA (with mean age, mass and height of 70.8 years ± 4.2, 85.4kg ± 8.5 and 173.8 cm ± 4.9 respectively), and 20 patients with unilateral 12 months post knee replacement (mean age, mass and height of 72 years ± 7.6, 83.5kg ± 11.5 and 169.2 cm ± 9.2 respectively.

B. Ground reaction forces Features

The GRFs were recorded while the subjects walked bare-footed at a self selected pace on a 10m walkway equipped with an embedded force platform (1000Hz, Kistler, type 9287, Winterthur, Switzerland) centrally positioned to define the stance phase.

C. Data Set

The GRFs of the affected leg were measured and normalised according to the subject's body weight (GRF/BW) while the stance phase data was time normalised, such that heel strike was 0% and foot/toe off was 100%. The GRF magnitudes and the time for peak GRFs were measured for vertical (the heel strike transient, first and second maximum peak and minimum trough), posterior and anterior peaks (features ID are presented in Table 1). The subject velocity was also recorded giving a total of 13 features per subject. Each class was divided into training and test data according to the ratio 4:1 resulting in a combined training set consisting of 20 examples and a test set of 8 examples. The training set was used for the construction of the multiclass SVM decision rule, while the test set was used to evaluate the SVM generalization performance.

TABLE 1: GAIT FEATURES USED TO DEFINE THE 3 KNEE PATHOLOGY CLASSES.

Number	ID	Feature Definition
1	**postgrf**	Peak posterior GRF
2	**antrgrf**	Peak anterior GRF
3	**vert1grf**	Peak vertical 1 GRF
4	**midvegrf**	Peak mid vertical GRF
5	**vert2grf**	Peak vertical 2 GRF
6	**tpostpea**	Time to peak posterior
7	**tantpeak**	Time to peak anterior
8	**tvpeak1**	Time to peak vertical 1
9	**tvmidpea**	Time to peak mid vertical
10	**tvpeak2**	Time to peak vertical 2
11	**heels**	Heel strike transient
12	**theels**	Time to heel strike transient
13	**vel**	Walking velocity

3. MULTICLASS SUPPORT VECTOR MACHINES

A. The Support Vector Machine Classifier

The SVM developed by Vapnik [11] and co-workers has been shown to be a powerful supervised learning method. The standard soft-margin Support Vector Machine is a binary classifier applied to classify data

$$\Theta=\{(\mathbf{x}_1, y_1), (\mathbf{x}_2, y_2)...(\mathbf{x}_l, y_l)\}$$
$$\mathbf{x}_i \in \mathbf{R}^n \qquad (1)$$
$$y_i = \{1, -1\}$$

where $\mathbf{x}_i$ are vectors containing the measurements or features of gait data and y_i are the corresponding class labels (i.e. +1=pathology, -1=healthy). The SVM classifier is a linear hyperplane which separates two classes where the distance between the class boundaries to the hyperplane is the hyperplane margin. Data that is not linearly separable is first mapped via a nonlinear function $\phi : \mathbf{x} \subset \Re^n \to \Re^m$ $n,m \in [1,\infty)$ to a higher dimensioned feature space. The optimal hyperplane is the universal approximator

$$f(x) = \sum_{i=1}^{l} w_i \phi(x_i) + b \qquad (2)$$

which is obtained by maximizing the margin of the hyperplane. The position of the hyperplane is determined by the weights, w_i and bias, b which are obtained by solving the following SVM quadratic programming problem:

$$\text{minimize } \Im(\mathbf{a}) = -\sum_{i=1}^{l}\alpha_i + \frac{1}{2}\sum_{i,j=1}^{l}\alpha_i\alpha_j y_i y_j K(x_i, x_j)$$
$$\text{subject to } \begin{cases} 0 \le \alpha_i \le C \\ \sum_{i=1}^{l}\alpha_i y_i = 0 \end{cases} \qquad (3)$$

Here α_i are Lagrangian multipliers and $K(\mathbf{x},\mathbf{y}) = \langle\phi(\mathbf{x}), \phi(y)\rangle$ is a kernel function. The process of solving the optimization problem is known as *training* the SVM and using the SVM to classify new data is known as *testing*. The parameter C controls the tradeoff between minimization of training error and maximization of generalization capability. The separating hyperplane is usually written in terms of the Lagrangian Multipliers as

$$f(x) = sign\left(\sum_{i=1}^{l}\alpha_i y_i K(x, x_i) + b\right) \qquad (4)$$

This means positive SVM outputs are labeled as class +1 and negative values as class -1.

B. The multiclass Support Vector Machine

TABLE 2: STATISTICAL MEAN AND STANDARD DEVIATION (STD) FOR CLASS 1, 2 AND 4. ROC SEPARABILITY FOR THE THREE POSSIBLE CLASSIFICATIONS IS ALSO SHOWN.

		postgrf	antrgrf	vert1grf	midvegrf	vert2grf	tpostpea	tantpeak	tvpeak1	tvmidpea	tvpeak2	heels	theels	vel
Mean	Class1	0.184	0.193	1.120	0.732	1.037	16.972	87.213	24.484	47.198	75.385	0.775	2.028	1.306
Std	Class1	0.034	0.026	0.124	0.079	0.046	3.306	1.678	3.339	4.235	2.312	0.294	0.953	0.161
Mean	Class2	0.164	0.164	1.079	0.776	0.964	15.390	85.540	23.362	46.372	72.455	0.659	1.824	1.350
Std	Class2	0.045	0.036	0.185	0.107	0.017	3.884	1.639	3.573	5.949	6.093	0.348	1.456	0.208
Mean	Class3	0.224	0.250	1.101	0.652	1.017	14.000	87.900	22.100	47.600	77.900	0.614	4.000	1.426
Std	Class3	0.042	0.043	0.187	0.142	0.168	3.771	2.424	2.331	3.273	2.514	0.121	2.108	0.093
ROC	1 v 2	0.703	0.781	0.703	0.641	0.906	0.578	0.781	0.547	0.516	0.656	0.641	0.625	0.578
ROC	1 v 3	0.794	0.894	0.613	0.688	0.525	0.713	0.603	0.725	0.556	0.744	0.750	0.819	0.753
ROC	2 v 3	0.850	0.925	0.675	0.775	0.875	0.675	0.825	0.650	0.525	0.825	0.575	0.825	0.638

The multiclass Support Vector Machine (SVM) is an extension of the standard binary SVM classifier to classify data with more than two classes. In this paper, we implement the one against one multiclass SVM variant and use the "Max Votes Winner" strategy [13]. Assume that there are k classes in the data set, then this multiclass SVM is built from a combination of

$$\frac{k(k-1)}{2}$$

SVM classifiers as seen in Figure 1. During testing, the test example $\mathbf{x}$ is presented to each binary classifier in turn and the computed class is noted. For example, if a binary SVM trained to classify class a and b determines $\mathbf{x}$ as being class a, then the vote for class a is increased by one, otherwise class b is incremented by one. The class with the most number of votes after all binary classifiers have been tested is then the determined class for $\mathbf{x}$.

C. *Methodology of Multiclass SVM Design*

We trained three SVM binary classifiers separately denoted as SVM(1v2), SVM(1v3) and SVM(2v3) given that our data set contained only 3 classes. Three separate data sets were prepared for each SVM containing a combination of two classes out from the three according to the model to be trained. The optimal parameter set for each SVM was then determined using the leave one out procedure. In this procedure, an arbitrary example is first excluded from the data set and used as a test example while the remaining data is used to train the SVM. This is repeated until all training examples have been individually tested on the SVM. The resulting accuracy is referred to as the leave one out (LOO) accuracy and is a robust metric for determining the quality of the SVM model. All SVM models were trained over the range $C = \{0.1, 1, 10, 100, 1000\}$ using the linear, polynomial and Gaussian kernels which are defined as follows:

TABLE 3: BEST LEAVE ONE OUT ACCURACIES, SENSITIVITIES, SPECIFICITIES AND ROC AREAS FOR THE THREE BINARY SVMS CLASSIFIERS USING LINEAR, GAUSSIAN AND POLYNOMIAL KERNELS TRAINED ON ALL 13 GAIT FEATURES.

	Kernel	Parameters	C	Accuracy	Sensitivity	Specificity	ROC
SVM (1 v 2)	Linear		0.1	70.00	0.88	0.00	0.33
	Gaussian	s=0.005	1.0	80.00	1.00	0.00	0.38
	Polynomial	d=2	1.0	20.00	0.00	1.00	0.34
SVM (1 v 3)	Linear		0.1	92.31	0.94	0.90	0.87
	Gaussian	s=0.005	10.0	88.46	0.94	0.80	0.93
	Polynomial	d=2	1.0	50.00	0.38	0.70	0.67
SVM (2 v 3)	Linear		1.00	64.29	0.25	0.80	0.28
	Gaussian	s=0.05	1.00	71.43	0.00	1.00	0.38
	Polynomial	d=3	1.00	78.57	0.75	0.80	0.78

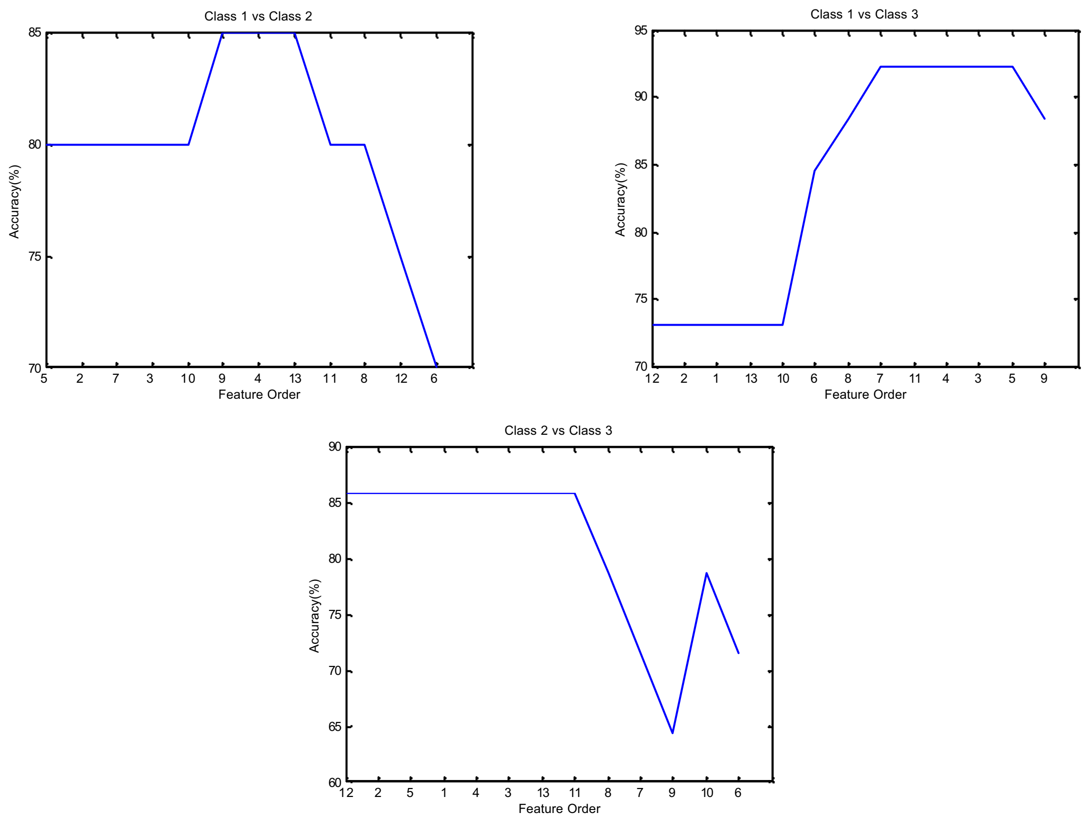

Figure 1: Leave one out accuracy plotted during feature selection using hill climbing algorithm. The order of optimal features found is depicted in the x-axis. All 3 SVM classifier models are shown.

$$K(x,z)_{linear} = x^T z$$
$$K(x,z)_{poly} = (2x^T z + 1)^d$$
$$K(x,z)_{gaussian} = e^{-s\|x-z\|^2}$$

where x, z are training vectors. The SVM architectures were trained and tested using the D2CSVM software found at http://www.ee.unimelb.edu.au/people/dlai. We used the area of the receiver operating characteristics (ROC) curve for single features to obtain a quantitative measure of individual feature separability. ROC areas were numerically approximated using the trapezoidal rule where larger values implied better linear individual feature separability.

In the following, we investigate the design of individual binary SVMs to obtain the best performing models. A feature selection algorithm is then applied to improve the model performance and the final multiclass SVM is constructed and tested on the test set.

4. Experimental Results

A. Statistical Analysis of Gait Features

We first investigated the statistical characteristics of the 13 features, computing the mean, standard deviation and ROC areas for the individual features. As seen from Table 2, the means for the GRF features varies between the three classes, suggesting that some features are similar for all classes and therefore have poor discriminative power. The individual ROC values in the range of 0.516-0.925 indicating the classes are not linearly separable using these features alone. The peak posterior and anterior GRFs have significantly higher ROC values for all three classes. This suggests that knee loading pattern during the braking and propulsion phases is different between the three knee pathologies.

B. Performance of the Binary SVM classifiers

Table 3 depicts the best performance for the individual classifiers over the linear, Gaussian and polynomial kernels used. It was found that the overall best LOO accuracy was achieved for the Class 1 versus Class 3 SVM suggesting that knee replacement gait was easier to recognize from PFPS gait using all 13 features. This was further reinforced by the similar sensitivities and specificities across the SVM models and high ROC areas (>0.8) indicating good separation.

The best result for differentiating knee replacement from OA gait (Class 1 versus Class 2) was 80% LOO accuracy. However, the Gaussian SVM in this case had very poor specificity and very bias towards recognizing Class 1. The best accuracies over other models were also biased towards recognizing one class. This could be due to the unbalanced data where Class 1 had 20 examples compared to Class 3,

TABLE 4: FEATURE SELECTION USING HILL-CLIMBING ALGORITHM TO DETERMINE SUBSET OF OPTIMAL FEATURES. THE ORDER OF OPTIMAL FEATURES FOUND IS PRESERVED

SVM model	Optimal Features in Order	Opt Acc	Kernel
1 v 2	1,5,2,7,3,10,9	85.00	Gaussian s=0.005, C=100
1 v 3	12,2,1,13,10,6,8,7,	92.31	Gaussian s=0.005, C=10
2 v 3	12,2	85.71	Gaussian s=0.05, C=10

which had only 5 examples, thereby causing the classifier to be mostly biased to the larger class. The recognition between Class 2 and 3 was lower suggesting that GRFs of OA and PFPS gait were relatively similar.

C. Feature Selection and Multiclass SVM performance

We next applied a hill-climbing feature selection algorithm to improve the performance of the binary SVM classifiers. This was done to obtain a more accurate multiclass decision rule and also to infer gait features that were significantly different between the pathologies.

Table 4 depicts the best LOO accuracies obtained for each binary SVM and the respective models. It can be seen that more features are required to successfully differentiate knee replacement gait (Class 1) from either OA gait or PFPS gait. The following features differentiated knee replacement gait from knee OA: peak anterior, posterior, vertical 1 and vertical 2 and time to peak of the anterior and peak vertical 1, 2 and mid vertical. Slightly different GRF features differentiated knee replacement gait and PFPS gait which also included the walking velocity and time to heel strike transient. However, only two features were adequate to discriminate OA from PFPS gait, these include time to heel strike transient and peak anterior GRF. Figure 1 depicts the order of selection for the features over the three binary SVMs. Results in Table 4 indicate vast improvements to the individual LOO accuracies which were now in the range of 85%-92%.

Using these features and SVM models, the multiclass decision rule was then constructed using the *Max Votes* rule. We tested the multiclass decision rule constructed from the best binary SVMs in the previous section and compared it against the rule constructed from classifiers after feature selection. The first rule performed poorly providing only 37.5% accuracy while the second multiclass SVM managed a better 62%. Considering that our test set consisted of only 8 examples, the best result corresponded to 3 errors which was encouraging considering that a significantly small number of OA subjects were available.

5. DISCUSSION

In this work, we have demonstrated that the multiclass SVM has the potential to successfully classify patients with different knee pathologies with a max leave one out (LOO) accuracy range 85% - 92%. It was found that the multiclass classifier was able to detect gait features of PFPS patients, knee OA and patients with knee replacement as indicated in Table 4. The optimal set of features which contributed to the classification of the three pathology groups was different between the classes, due to the different pattern of knee joint loading between the groups.

The classifier detected 7 and 8 features related to the peak GRFs and their relative timing as being sensitive to distinguish between patients with knee replacement and both knee OA and PFPS (Class 1 vs Class 2 and Class 1 vs Class 3 respectively). Interestingly, the application of the SVM between knee OA and PFPS (Class 2 vs Class 3) revealed only 2 features (peak anterior GRF and time to heel strike transient) as being different between the two classes. This may indicate that the knee loading of patients with PFPS and knee OA may be more similar to each other than the loading with knee replacement. Since both PFPS and knee OA result in pain and disability at the knee joint, these patients may alter their gait to reduce the load in the asymptomatic leg.

The classification between knee replacement and knee OA detected that the peak vertical and anterior-posterior GRFs discriminated between the classes. The magnitude of the GRFs was smaller for the knee OA group. Since knee replacement surgery improves mobility and function as well as reduction in pain [3], improvement in gait function is also expected [14]. The magnitude of the anterior and posterior GRFs was larger, however, for the PFPS group when comparing between PFPS and knee replacement groups. The SVM detected the velocity as part of the 8 GRFs features as being different between the groups, indicating slightly faster walking speed for the PFPS group. The difference in the walking velocity may have affected the magnitude of the GRFs.

6. CONCLUSION

In this research, muliclass SVM was applied to recognize gait patterns of patients with different knee pathologies: PFPS, knee OA, and knee replacement using GRFs. The SVM classifier was able to effectively recognize gait parameters that are altered due to the various knee pathology conditions. This suggests that GRF information are affected by abnormal joint loading to the extent that they can be detected using the multiclass SVM.

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