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# Support Vector Machines for detecting recovery from knee replacement surgery using quantitative gait measures

Pazit Levinger, Daniel T.H. Lai, Kate Webster, Rezaul K. Begg, *Senior Member, IEEE*, Julian Feller.

**Abstract— Knee osteoarthritis (OA) is one of the leading causes of disability among the elderly which, depending on severity, may require surgical intervention. Knee replacement surgery provides pain relief and improves physical function including gait. Gait dysfunction such as altered spatio-temporal measures and gait asymmetry both pre- and post-surgery, however, may still persist after the surgery. In this paper, we investigated the application of Support Vector Machines (SVM) to classify gait patterns pertaining to knee OA before surgery based on spatio-temporal gait parameters and to investigate whether SVM can assess gait improvement at 2 months following knee replacement surgery. Test results indicate that the SVM can identify the OA gait from the healthy ones with a max leave one out (LOO) accuracy of 94.2%. When feature selection technique was applied, the accuracy improved to 97.1% using only 2 symmetry index features. Further, the post surgery test results by the SVM indicated 4 patients still had altered gait. This suggests that subject gait symmetry should be monitored closely after surgery to assess treatment outcomes and recovery.**

## I. INTRODUCTION

Knee osteoarthritis (OA) is one of the leading causes of disability among people aged 65 years and over in Australia [1]. Individuals with knee OA suffer from pain, stiffness and physical disability 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].

Quantitative measures of gait can aid in the identification of potential fallers and predict functional status [4, 5]. Since, normal walking patterns are adversely affected by lower extremity joint disease; spatio-temporal parameters have clinical relevance in the assessment of motor pathologies particularly in orthopaedics. Spatio-temporal gait parameters, therefore, have been frequently used in a clinical setting.

Knee replacement surgery has been reported to improve the gait patterns of patients with OA. However gait dysfunction, including gait symmetry may still persist after the surgery [6-8]. Quantitative measures of gait such as spatio-temporal measures may be used as markers of the integrity of a person's locomotor ability and should be monitored after surgical intervention. Since gait dysfunction can lead to reduced physical activity levels, mobility and independence, an understanding how gait patterns of patients with knee OA and those who undergo unilateral knee replacement differs from normal may help target pre and postoperative physical therapy for improving and preventing knee OA.

In this paper, we investigated the automated recognition of subjects with OA using the Support Vector Machine (SVM) based on spatio-temporal gait parameters. We then employed the SVM to assess the gait pattern of patients after knee replacement surgery. SVMs are powerful nonlinear classifiers based on statistical learning theory [9] which have been successfully used in various pattern recognition problems [10]. Our objective was to investigate if these variables can discriminate the pathology from the healthy subjects and to determine the subset of variables that best describe OA gait. Furthermore, we investigated whether the SVM can assess any gait improvement 2 months following surgical intervention. In the following, section 2 describes our data collection process and gives an overview of the SVM formulation. Our experimental results and discussion are contained in section 3 and 4 respectively.

## II. METHODS

### A. Knee Osteoarthritis Data

The study consisted of two groups: healthy control and symptomatic subjects who had undergone knee replacement. The subjects from the control group were obtained from a research database within the Musculoskeletal Research Centre, La Trobe University. The control group (6 females and 6 males) had a mean age, mass, height and body mass index (BMI) of 81.5 ± 4.6 years, 68.1 ± 15.6 kg, 166.4 ± 0.1 cm and 24.3 ± 2.5 kg·m$^{-2}$ respectively. The symptomatic groups included 11 patients (2 females and 9 males) who had undergone unilateral knee replacement surgery for the primary diagnosis of osteoarthritis. The symptomatic group had a mean age, mass, height and body mass index (BMI) of 69.2 ± 6.4 years, 81.3 ± 11.3 kg, 173.2 ± 0.1 cm and 28.1 ± 2.3 kg·m$^{-2}$ respectively. All subjects from the symptomatic

Mauscript received April 2 2007. Pazit Levinger is with the Musculoskeletal Research Centre, Gait CCRE, La Trobe University, VIC 3086, Australia.; pazit_levinger@yahoo.com.au (corresponding author).

Daniel T.H. Lai is with the Department of Electrical & Electronic Engineering, The University of Melbourne, VIC 3010, Australia

Kate Webster is with the Musculoskeletal Research Centre, Gait CCRE, La Trobe University, VIC 3086, Australia

Rezaul K. Begg is with the Biomechanics Unit, Centre for Ageing, Rehabilitation, Exercise and Sport, Victoria University, VIC 8001, Australia.

Julian Feller is with the Musculoskeletal Research Centre, Gait CCRE, La Trobe University, VIC 3086, Australia

group were tested 2 months prior to undergoing knee replacement surgery, 10 subjects were tested again 2 months post surgery. Patients were excluded if they had uncontrolled systemic disease, previous knee surgery and a pre-existing neurological or other orthopaedic condition affecting walking. Clinical assessment, which evaluated the knee joint of the operated limb, was performed pre and post operatively using the Knee score [11]. The knee score gives a value between 0 to 50, where 50 points represents a well aligned knee with full range of motion and good stability.

Spatio-temporal parameters of the symptomatic group during level walking were recorded using a three-dimensional motion analysis system (Vicon 512, Oxford Metrics, Oxford, UK) with 6 cameras (50Hz). The vertical ground reaction force was captured using a Kistler force plate (400 Hz) and was used to define the stance phase. Infrared retro reflective markers (25mm) were attached to anatomical locations on the lower extremity and Vicon Plug-in Gait (Oxford Metrics) biomechanical modeling software was used to process and output spatio-temporal parameters.

The spatio-temporal parameters of the control group were recorded using an instrumented mat (GAITRite CIR system Inc, Havertown, PA, USA). The mat consists of a flat instrumented walkway with a series of embedded pressure sensitive switches connected to a computer installed with GAITRite application software [12, 13]. The GaitRite system was reported as a valid tool for assessing spatio-temporal parameters when compared to a three-dimensional motion analysis system (Vicon) [12]. Subjects were instructed to walk barefoot at a self-selected speed and three walking trials for each limb were used for the data analysis

The following spatio-temporal parameters were recorded and used for the analysis: walking velocity, cadence, stride length and stride time. The stride length was normalized to the subject's height. The absolute value of the symmetry index (SI) of step length, step time, single support time and double support time was also used for the analysis and were calculated [14]. Three trials were taken from each subject for the analysis with a total training data of 69 (12 healthy and 11 symptomatic). The symptomatic subjects (OA) were labeled as +1 and -1 indicated healthy subjects.

### *B. Support Vector Machine Classifier*

The SVM developed by Vapnik [15] 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

$$\begin{aligned}&\Theta=\{(\mathbf{x}_1, y_1), (\mathbf{x}_2, y_2)...(\mathbf{x}_l, y_l)\}\\&\mathbf{x}_i \in \mathbb{R}^n\\&y_i=\{1,-1\}\end{aligned} \qquad (1.1)$$

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

$$f(x)=\sum_{i=1}^{l} w_i\phi(x_i)+b \qquad (1.2)$$

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:

$$\begin{aligned}&\text{minimize } \Im(\boldsymbol{\alpha})=-\sum_{i=1}^{l}\alpha_i+\frac{1}{2}\sum_{i,j=1}^{l}\alpha_i\alpha_j y_i y_j K(x_i,x_j)\\&\text{subject to } \begin{cases}0\le\alpha_i\le C\\ \sum_{i=1}^{l}\alpha_i y_i=0\end{cases}\end{aligned} \qquad (1.3)$$

Here $\alpha_i$ 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

$$f(x)=sign\left(\sum_{i=1}^{l}\alpha_i y_i K(x,x_i)+b\right) \qquad (1.4)$$

### *C. Methodology of SVM design*

The optimal SVM parameter set was determined using the leave one out procedure where an arbitrary example was excluded from the training data and used as a test example. This was repeated until all training examples were individually tested on the SVM. The average accuracy is 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 $0.1\le C\le 100$ using the linear, polynomial and Gaussian kernels defined as follows

$$K(x,z)_{linear}=x^T z$$

$$K(x,z)_{poly}=(2x^T z+1)^d$$

$$K(x,z)_{gaussian}=e^{-s\|x-z\|^2}$$

where $x,z$ are training vectors. The SVM architectures were trained and tested on a 1.6 GHz Celeron 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 feature separability.

TABLE 1: STATISTICAL ANALYSIS AND ROC VALUES OF INDIVIDUAL FEATURES FOR THE SYMPTOMATIC GROUP (OA) AND THE CONTROL GROUP.

| | Spatio-temporal parameters | | | | Symmetry Index | | | |
|---|---|---|---|---|---|---|---|---|
| | Velocity m/s | Cadence step/min | Stride length m | Stride time sec | Step length | Step time | Single support | Double Support |
| Mean OA | 1.156 | 105.394 | 0.757 | 1.147 | 6.614 | 5.916 | 6.454 | 6.917 |
| Std OA | 0.175 | 9.759 | 0.090 | 0.134 | 4.373 | 5.889 | 5.206 | 7.192 |
| Mean Control | 1.162 | 110.711 | 0.760 | 1.094 | 3.919 | 2.466 | 3.148 | 2.571 |
| Std Control | 0.138 | 10.701 | 0.063 | 0.099 | 2.571 | 0.987 | 1.211 | 1.063 |
| ROC Area | 0.524 | 0.582 | 0.535 | 0.589 | 0.708 | 0.688 | 0.699 | 0.727 |

### A. *Experimental Results*

#### 1) *Statistical Analysis of spatio-temporal features*

We first investigated the statistical characteristics of the 8 features, computing the mean, standard deviation and ROC areas for the individual features. As seen from Table 1, the means for velocity, cadence, stride length and stride time do not differ, suggesting that they are similar for both classes and therefore have poor discriminative power. This is confirmed further by individual ROC values in the range of 0.524-0.589 indicating the two classes are not linearly separable using these features alone. The symmetry indexes of step length step time, single support and double support features have significantly higher ROC values, that is larger than 0.65. This suggests that the asymmetry index of the temporal measures: single support and double support is greater in patients with OA, since these patients spend a greater portion of the gait cycle on the non-operated leg. It was also found that the values of cadence were much larger in magnitude than the other features. Thus all features were normalized to zero mean and unit standard deviation to facilitate the training of SVMs [15].

TABLE 2: BEST LOO ACCURACIES, SENSITIVITIES AND SPECIFICITIES FOR VARIOUS SVM KERNEL PARAMETERS

| Kernel | C | LOO Acc (%) | Sens | Spec |
|---|---|---|---|---|
| Linear | 0.1 | 91.30 | 0.82 | 1.00 |
| G (s=0.005) | 100 | 91.30 | 0.85 | 0.97 |
| G (s=0.05) | 1 | 92.75 | 0.88 | 0.97 |
| G (s=0.5) | 10 | **94.20** | 1.00 | 0.89 |
| Poly (d=2) | 1000 | 89.86 | 0.82 | 0.97 |
| Poly (d=3) | 1000 | 52.17 | 0.00 | 1.00 |

#### 2) *SVM Classification and Feature Selection*

It was found that all 8 input features produced a maximum LOO accuracy of 94.2% using a SVM with Gaussian kernel, s=0.5 and C=10. Due to space constraints, we report only the best accuracies over the range of SVM kernels (Table 2) where on average, the Gaussian kernel was found to provide better classification compared to the polynomial and linear kernels. The SVM was better overall at detecting the healthy subjects compared to the OA gait as depicted by the higher specificities.

We then ran the hill climbing feature selection algorithm [10] to investigate if further classification improvements were possible. The algorithm began with the double support symmetry, which had the highest ROC area i.e., 0.727 and the remaining features were sequentially combined to obtain the maximum LOO accuracy (Figure 1). It was found that only two features were required to produce the maximum LOO accuracy of 97.1% (Table 2) after which no further improvement in accuracy was obtained. These two features were the double and single support symmetry indexes, suggesting that symmetry measures had sufficient discriminative power to accurately classify the two groups.

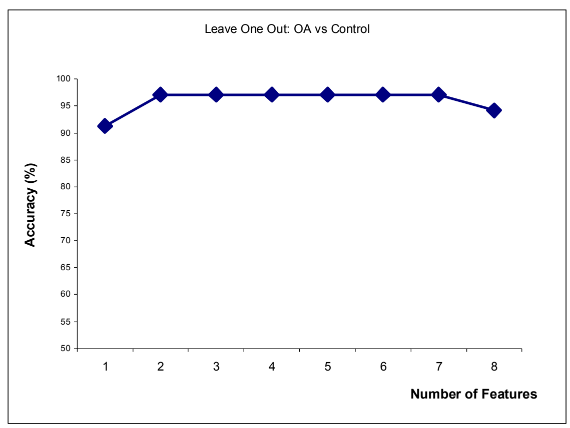


Figure 1: Variation of leave one out accuracy obtained from the hill-climbing feature selection algorithm.

#### 3) *SVM prediction for post surgery recovery*

We then applied this SVM model to identify the gait patterns of the patients 2 months post surgery. The SVM detected 4 patients out of 10 that still possessed gait characteristics similar to OA gait 2 months post surgery. It is however possible that some of the patients did not recover fully from the operation at 2 months post operation. The knee score of these patients ranged 43-48 and 36-46 pre and post operation respectively, indicating a slight reduction in the knee score postoperatively.

## B. Discussion

The SVM classifier detected symmetry index of single and double support time as being sensitive to distinguish between gait of patients with OA and healthy controls. This may suggest that symmetry gait measures may be used to evaluate patients with knee OA. In previous studies, gait alterations including gait asymmetry have been observed in patients with knee OA pre and post surgery [6-8], suggesting that an asymmetric gait pattern may be a subconscious compensation strategy to reduce the load in the operated limb. Therefore, asymmetric gait measures may be monitored after surgery to assess treatment outcome and recovery.

Improvement in the spatio-temporal measures has been reported after knee replacement [16]. Some patients, however, do not recover completely normal walking patterns [17, 18]. It is possible that an initial gait adaptation occurs in response to knee pain and possibly structural disease before the surgery which persists postoperatively. The SVM classifier detected that 4 of the 10 subjects still had altered gait parameters 2 months after the surgery similar to the OA gait pattern. This suggests that these subjects perhaps did not gain gait patterns similar to the control group. It is, however, also possible that some of the current patients did not recover fully from the operation at 2 months post operation. This is supported by the clinical assessment of the operated knee of these patients which showed a slight reduction of the knee score at 2 months following the surgery compared to the pre operation value. This suggests that the SVM classifier was able to effectively identify any improvement in gait patterns or otherwise altered gait following the surgery.

# III. Conclusion

In this research, an artificial intelligence approach (SVM) was applied to recognize gait patterns of patients with knee OA before and after knee replacement surgery using spatio-temporal gait parameters. The SVM classifier was able to effectively recognize gait parameters that are altered due to knee OA condition before knee replacement surgery using two gait parameters (97% accuracy). Furthermore, the SVM detected improvement in gait function due to surgical intervention at 2 months following knee replacement. These results have clinical relevance in the assessment of knee OA, suggesting that gait measures should be monitored after surgery to assess treatment outcome and recovery.

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