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A machine learning approach to *k*-step look-ahead prediction of gait variables from acceleration data

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***Abstract*— This paper investigates the use of machine learning to predict a sensitive gait parameter based on acceleration information from previous gait cycles. We investigate a *k*-step look-ahead prediction which attempts to predict gait variable values based on acceleration information in the current gait cycle. The variable is the minimum toe clearance which has been demonstrated to be a sensitive falls risk predictor. Toe clearance data was collected under normal walking conditions and 9 features consisting of peak acceleration and their normalized occurrences times were extracted. A standard least squares estimator, a generalized regression neural network (GRNN) and a support vector regressor (SVR) were trained using 60% of the data to estimate the minimum toe clearance and the remaining 40% was used to validate the model. It was found that when the training data contained data from all subjects (inter-subject) the best GRNN model provided a root mean square error (RMSE) of 2.8mm, the best SVR had RMSE of 2.7mm while the standard least squares linear regression method obtained 3.3mm. When the training and test data consisted of different subject examples (inter-subject) data, the linear SVR demonstrated superior generalization capability (RMSE=3.3mm) compared to other competing models. Validation accuracies up to 5-step look-ahead predictions revealed robust performances for both GRNN and SVR models with no clear degradation in prediction accuracy.**

I. Introduction

Gait analysis is the biomechanical study of the lower limbs during locomotion. Clinicians have been frequently faced with the daunting prospect of processing and interpreting large volumes of data usually collected over several gait cycles. A recent paradigm which is gaining recognition for dealing with large data in this field is machine learning; which comprises computational intelligence techniques such as artificial neural networks, support vector machines and fuzzy methods [1].

These techniques permit the modeling of relationships between measured quantities, e.g. limb displacements and the required information of interest e.g., maximum joint angles or peak ground reaction forces. They have been successfully applied to many problems such as detecting quadriceps muscle activity [2] and in predicting joint angles and limb kinematics [3]. Recent work by Findlowa et al. focused mainly on predicting entire gait data curves by feeding the data series into a regression model. The technique exhibited a high degree of success for intra-subject data (training and testing data were from the same group of subjects) but poor generalization to inter-subject (training and testing data from different groups of subjects) predictions. It required large input data dimensionalities and the predicted curves still had to be post processed to obtain the gait variables of interest i.e., limb kinematics.

In this work, we investigate the use of machine learning to predict gait variable values based on a *k*-step look ahead procedure. The idea is to model the relationships between accelerations in the current gait cycle and the value of a gait variable *k* gait cycles ahead under the assumption that the subject walks the further *k*-steps. We focus on the prediction of the minimum toe clearance (MTC), a parameter which has been demonstrated to be a sensitive falls risk predictor [4]. In this preliminary paper, we use toe acceleration data obtained from toe displacement measurements made by a highly accurate video capture system. The generalized regression neural network (GRNN) and Support Vector Regressor (SVR) were then compared against the ordinary least squares regression to assess their effectiveness.

Section II details the data collection methods, preprocessing and provides a brief background of the machine learning methods investigated. Section III provides the experimental results followed by discussions and conclusions.

Figure 1: Experimental setup for monitoring toe displacement data with the Optotrak system.

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II. METHODS

A. Gait Data Collection

Experiments were performed in the Biomechanics Laboratory of Victoria University and gait data was collected from 5 healthy subjects (4 male and 1 female) who were 28-35 years of age. The subjects had no prior gait disabilities. Data collection was performed with the Optotrak Certus NDI video camera system sampled at 150Hz. Subjects wore a rigid marker body on the right foot and a virtual point was placed at the distal shoe representing toe motion (Figure 1).

The subjects walked on a treadmill at three speeds, namely 2.5, 3.5 and 4.5km/h for 5 minutes so that at least 100 gait cycles were collected. The toe off gait events were detected and used to mark consecutive gait cycles. The MTC points were extracted using a gradient algorithm and visually checked. Briefly, the MTC point is defined as the minimum point between the Max 1 and Max 2 peaks (Figure 2). It is the lowest point during the mid-swing phase of the gait cycle.

B. Feature Extraction

Each gait cycle was differentiated twice to obtain the acceleration graph. The acceleration series was then low-pass filtered (cut-off frequency 12Hz) twice using a 2nd order Butterworth filter to ensure zero phase shift and to remove differentiation noise [5]. Filtering was achieved using the MATLAB v7.1 filter toolbox.

For each gait cycle acceleration graph, five major peaks were detected, namely AVMAX1, AVMAX2, AVMAX3, AVMIN1 and AVMIN2 (Figure 3). The normalized time to peak t_{peak} was calculated as follows:

$$t_{peak} = \frac{n_{peak}}{n_{total}} \times 100\% \tag{1.1}$$

where n_{peak} was the number of samples from toe off to where the peak occurred and n_{total} was the number of samples in the gait cycle. Four periods, $t_1 - t_4$ corresponding to the occurrences of AVMAX2, AVMAX3, AVMIN1 and AVMIN2 were extracted. The time due to toe off acceleration was the origin point and hence not included. Each example or feature vector then consisted of 9 features.

A total of 2325 gait cycles were obtained from the five subjects with each subject averaging 465 consecutive gait cycles. 5 datasets labeled D1-D5 were formed from this data as follows; for D*k* the MTC value for gait cycle *n* was paired with acceleration features from gait cycle *n-k* so that dataset D1 contains data examples where acceleration information from gait cycle *n*-1 is used to predict the MTC at gait cycle *n*. The data was then divided into training and test sets under two conditions. In the first condition, both training and test sets contained examples from all subjects (intra

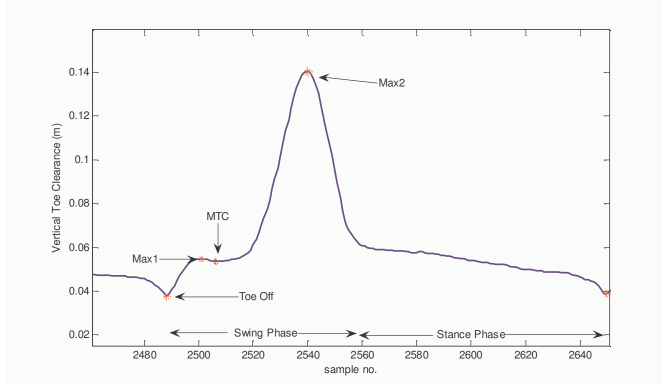

Figure 2: Sample toe displacement graph obtained from Optotrak system with the MTC, Max1 and Max2 points marked.

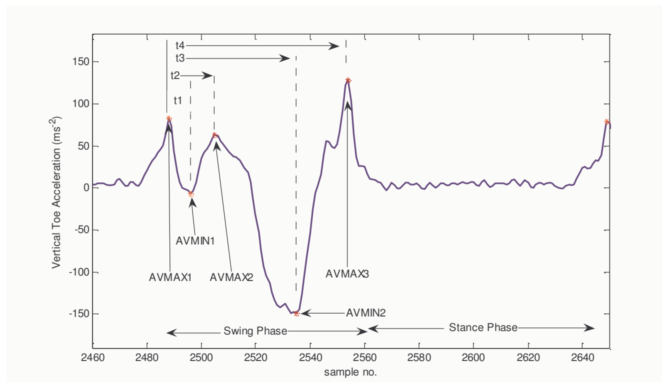

Figure 3: Sample acceleration graph corresponding to Figure 1 obtained by double differentiation and zero phase low pass filtering. The extracted features are marked and shown.

-subject condition) while in the second condition, the training and test sets were from different subjects (inter-subject condition). Train and test ratios were fixed to 3:2.

C. Regression Models

The dataset can be represented as training pairs $Dk = \{(y_1, \mathbf{x}_1),...,(y_n, \mathbf{x}_n)\}$ where y_i is the MTC value *k*-steps ahead and $\mathbf{x}_i$ the feature vector for the current gait cycle. The following regression models were investigated in this paper:

1) Least Squares Regression

The standard least squares regression was implemented in MATLAB. The following least squares problem was solved using matrix inversions:

$$\min \sum_i (y_i - \mathbf{w}^T \mathbf{x}_i)^2 \tag{1.2}$$

where $\mathbf{w}$ is the vector of weights or the solution of (1.2).

2) Generalized Regression Neural Networks (GRNN)

The GRNN model consists of a radial basis layer and a special linear layer [6]. The estimated MTC value $\tilde{y}$ is obtained by solving the following equation:

$$\tilde{y} = \frac{\sum_{i=1}^{n} y_i e^{\frac{-\|x-x_i\|^2}{2\sigma^2}}}{\sum_{i=1}^{n} e^{\frac{-\|x-x_i\|^2}{2\sigma^2}}} \qquad (1.3)$$

where σ is the width of the radial basis function. The GRNN was implemented in MATLAB which required the user to select a parameter known as the spread, s. The spread is defined as the distance an input vector must be from the neuron weight vector to be 0.5. In our experiments, the network was trained for spread values of 1 to 50 in steps of 0.2. The training results are depicted in Figure 3 and Figure 4 for both inter-subject and intra-subject conditions and the GRNN models with the lowest training error was selected.

3) *Support Vector Machine Regression*

The Support Vector Regressor (SVR) is a realization of Vapnik's Structural Risk Minimization theory [7]. We employ Vapnik's ε-insenstive loss SVR model where the MTC corresponding to feature vector $\mathbf{x}$ is predicted by

$$\tilde{y}(\mathbf{x}) = \sum_i K(\mathbf{x}, \mathbf{x}_i)\alpha_i + b \qquad (1.4)$$

where α_i are Lagrangian multipliers obtained by solving:

$$\min_{\alpha} \frac{1}{2}\boldsymbol{\alpha}^T \mathbf{K}\boldsymbol{\alpha} + \varepsilon|\boldsymbol{\alpha}|^T \mathbf{1} - \boldsymbol{\alpha}^T \mathbf{y} \qquad (1.5)$$

subject to: $-\mathrm{C} \le \alpha \le \mathrm{C}$, $\boldsymbol{\alpha}^T \mathbf{1} = 0$

Here the SVR parameters to be selected are ε the width of the insensitive zone, the regularization parameter C and the kernel function $K(\mathbf{x}, \mathbf{z})$ which maps input feature vectors to a usually higher dimensional feature space. In this work, we used the linear, polynomial and Gaussian kernels defined as:

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

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

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

with Gaussian widths, s=0.5,0.05 and 0.005 and polynomial degree d=2,3 and 4. For each kernel setting, the SVR was trained and tested over C=0.1,1,10,100,1000 and $\varepsilon = 0.1 - 0.8$ in steps of 0.1. Due to space constraints only the SVR model for each kernel which gave the highest test set accuracy is reported.

III. EXPERIMENTAL RESULTS

The training results in Figure 4 indicate that the GRNN network achieved minimum training error for spreads in the region of s=10 with minimum root mean square error of 3.00mm. The trend was similar for 2-step to 5-step look-ahead predictions with the intra-subject data. In Figure 5, the best GRNN performances were located for models with

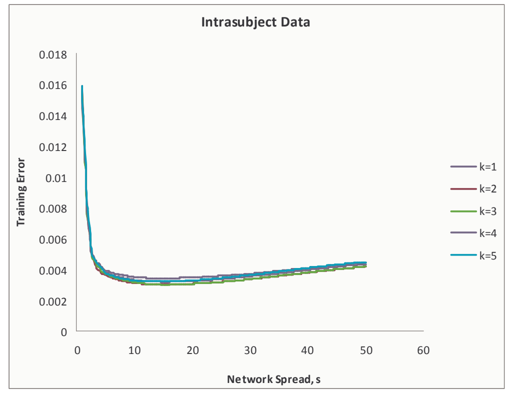

Figure 4: Training error of the GRNN as network spread is varied for intrasubject data for k=1-5.

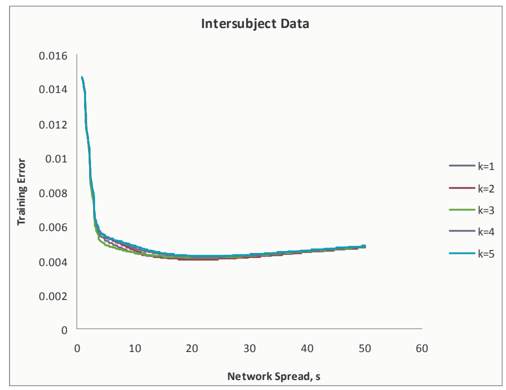

Figure 5: Training error of the GRNN as network spread is varied for intersubject data for k=1-5.

s=16 and the average minimum RMSE was 4.03mm. The trend of the training errors were also similar for k=1 to k=5 for the inter-subject data.

Table I depicts the best test data results for the three regression models for the intrasubject data. The least squares regressor achieved an average RMSE of 3.38mm across the k-steps, the GRNN achieved 3.12mm average RMSE while the polynomial SVR achieved average RMSE values of 3.16mm for predictions of MTC values based on the previous k gait cycle acceleration features. When intersubject data was used, the average RMSE were found to be increased for the standard least squares regressor (3.43mm) and GRNN (4.14mm) as seen in Table II. The SVR models achieved lower RMSE values with the best model being the linear SVR model (average RMSE=3.34mm) followed by the Gaussian and polynomial models.

IV. DISCUSSION

The results demonstrated that both the GRNN and SVR methods can be used to predict the MTC values to a very high degree of accuracy. Good prediction results were achieved for intra-subject data, however the accuracies were decreased for all models in the inter-subject This finding lends some evidence that the SVR possesses superior

TABLE 1: ROOT MEAN SQUARE ERROR (MM) FOR INTRA-SUBJECT EXPERIMENTS FOR *K*-LOOK AHEAD PREDICTION OF MINIMUM TOE CLERANCE VALUES

k	1	2	3	4	5
LS Regression	3.30	3.42	3.30	3.30	3.59
GRNN	3.00	3.20	3.02	3.00	3.40
SVR Linear	3.25	3.43	3.30	3.39	3.59
SVR Gaussian	3.01	3.38	3.11	3.19	3.36
SVR Polynomial	3.27	3.22	2.97	3.01	3.35

TABLE 2: ROOT MEAN SQUARE ERROR (MM) FOR INTER-SUBJECT EXPERIMENTS FOR *K*-LOOK AHEAD PREDICTION OF MINIMUM TOE CLERANCE VALUES

k	1	2	3	4	5
LS Regression	3.43	3.41	3.43	3.42	3.46
GRNN	4.08	4.03	4.15	4.20	4.24
SVR Linear	3.29	3.33	3.37	3.36	3.37
SVR Gaussian	4.00	3.79	3.51	3.82	3.82
SVR Polynomial	3.97	4.21	3.60	3.89	3.98

generalization capabilities and would be our first choice for future work. The poorer performance of the GRNN among the models could be attributed to the fact that like most neural network architectures, it is also affected by local minima resulting in sub-optimal models.

The overall results however indicate that there is lower variability in the subject's gait since the accuracy of predictions do not significantly change across the prediction horizon. The methods are encouraging but further work is required to ascertain the extensibility of these methods. Firstly a larger subject population is required to obtain an increased variability in gait data. In addition, different subject populations such as the young and elderly or subjects with pathological gait are hypothesized to pose greater challenges for these methods.

If further work is successful, these methods can be applied to research in wearable sensor technologies for monitoring human motion. For example, current inertial sensors such as accelerometers and gyroscopes suffer from drift errors which affect the derivation of linear velocity and displacement [8]. Several solutions have been proposed which neither fully achieves the accuracies expected by clinicians nor into account the fact that clinicians are frequently only interested in specific gait variables, such as maximum foot plantar-flexion or maximum heel ground reaction force for analysis.

V. CONCLUSION

Machine learning techniques such as the GRNN and SVR have been found to be powerful predictors for the minimum toe clearance using peak acceleration features and normalized time values. The results are promising because the techniques do not require large computational overhead and can be applied in onboard implementations of wearable sensor and actuator technologies.

VI. REFERENCES

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