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Estimation of End Point Foot Clearance Points From Inertial Sensor Data

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Abstract— **Foot clearance parameters provide useful insight into tripping risks during walking. This paper proposes a technique for the estimate of key foot clearance parameters using inertial sensor (accelerometers and gyroscopes) data. Fifteen features were extracted from raw inertial sensor measurements, and a regression model was used to estimate two key foot clearance parameters: First maximum vertical clearance (mx1) after toe-off and the Minimum Toe Clearance (MTC) of the swing foot. Comparisons are made against measurements obtained using an optoelectronic motion capture system (Optotrak), at 4 different walking speeds. General Regression Neural Networks (GRNN) were used to estimate the desired parameters from the sensor features. Eight subjects foot clearance data were examined and a Leave-one-subject-out (LOSO) method was used to select the best model. The best average Root Mean Square Errors (RMSE) across all subjects obtained using all sensor features at the maximum speed for mx1 was 5.32 mm and for MTC was 4.04 mm. Further application of a hill-climbing feature selection technique resulted in 0.54-21.93% improvement in RMSE and required fewer input features. The results demonstrated that using raw inertial sensor data with regression models and feature selection could accurately estimate key foot clearance parameters.**

I. INTRODUCTION

The demand for real time and continuous gait monitoring while patients perform everyday activities in uncontrolled natural environments is rapidly increasing. Conventional motion analysis systems such as optoelectronic motion tracking systems produce highly accurate and precise kinematic measurements. However they cannot be used outside the laboratory, require professional supervision to operate, and are very expensive to acquire and maintain. Micro-Electro-Mechanical systems (MEMS) Inertial Measurement Units (IMU) are the new substitute to camera based motion analysis systems, because they are physically compact, light weight, easy to use, and cost effective [1].

Several studies examined IMU to characterize gait abnormalities by analysing physical pitch, roll, and yaw rotations of foot during walking [2]and to detect falls by monitoring the centre of mass of the body or by using threshold based accelerometer/ gyroscope algorithms [3], [4]. As IMUs suffer from noise and drift errors due to intrinsic physical sensor properties, obtaining kinematics information such as velocities and displacement directly remains a major challenge [5]. Therefore, there is an urgent need for devising alternative techniques to obtain displacement data from sensor based kinematic measurements [6], [7].

Fig. 1 depicts the vertical end point trajectory of the swing foot illustrating the key events and points: toe-off, First maximum vertical clearance after toe-off (mx1), Minimum Toe Clearance (MTC), maximum clearance (mx2) and heel-contact. MTC is considered as the key event for tripping as at MTC the vertical foot clearance is very low (1-2cm) above walking surface and foots forward velocity is approximately 3 times the velocity of the body centre of mass. Using mathematical models Lai et al. [8] predicted MTC from peak accelerations of the foot trajectory data obtained by an optoelectronic motion tracking system and demonstrated positive results especially when a 5-step look-ahead procedure was applied. This motivated our work to investigate if the technique could be extended to estimating the key end point foot trajectory points from the acceleration measurements directly obtained from IMU.

A preliminary study to understand the relationship between the inertial sensor data and the end point foot trajectory revealed relatively high correlations for mx1 and MTC during toe-off and just (0.06s) before toe-off [9]. This study therefore focuses on inertial sensor features extracted around the toe-off event to estimate mx1 and MTC. mx2 prediction was not attempted due to its low correlation with inertial

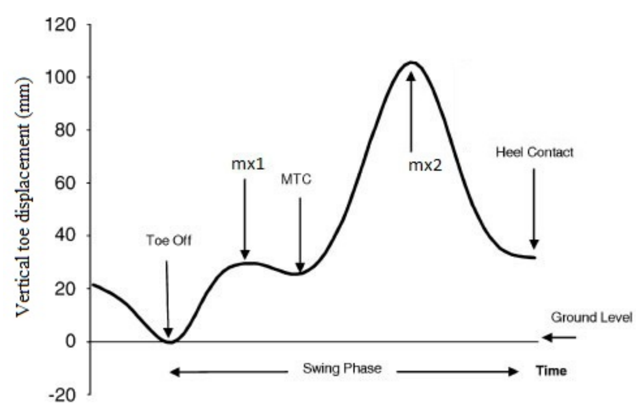

Fig. 1. Vertical displacement of the foot trajectory during the swing phase. Toe-off, mx1, MTC, mx2 and heel-contact events are illustrated during the swing phase of the gait cycle.

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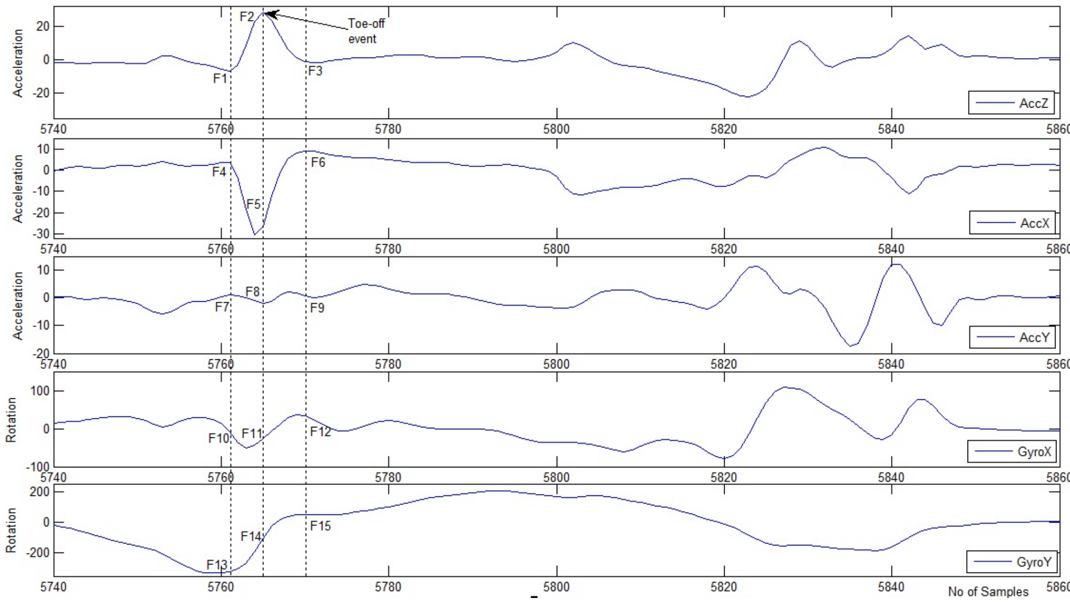

Fig. 3. Features extraction from AccZ data and corresponding extractions from AccX, AccY, GyroX, and GyroY at the same instance. Accelerations are given in m/s^2 and rotations are given in °/s

Fig. 2. Rigid body and inertial sensor arrangement on the shoe

sensor data [9], and also mx2 is not considered to be a major tripping risk event.

Section II of this paper describes the experimental setup and data processing techniques. Section III outlines the experimental results and Section IV elaborates on the results and followed by the conclusion

II. METHODOLOGY

A. Experimental Protocol

Eight healthy young subjects (5 males and 3 females; age range 25-35 years), without any known gait disorders were tested in the Biomechanics Laboratory of Victoria University. Subjects wore a rigid body with 4 active IRED markers positioned on the distal end of the right shoe. A virtual point was digitized (indicative of the lowest point under the shoe) as shown in Fig. 2. The active markers were tracked by an Optotrak Certus NDI camera system and sampled at 150Hz.

A 5DOF IMU consisting of a tri-axes accelerometer (Analog Devices, ADXL330) with ±3g range, 500Hz bandwidth, 330 mV/g sensitivity and a dual-axis gyroscope (InvenSense IDG-300) with a maximum sensitivity of 500°/s, a constant zero rotation at 1.5V at a regulated voltage supply of 3.3V was attached to the side of the rigid body. It was connected to a National Instruments DAQ board and sampled at 150 Hz.

All subjects walked on a motorized treadmill at 4 different walking speeds (2.5, 3.5, 4.5 and 5.5 km/h), each speed condition lasted for 5 minutes with the experimental protocol followed in [9].

B. Data Processing

Toe-off events were identified in the foot displacement trajectory data and sensor data using anterior-posterior displacement and maximum toe angular velocity measures [9]. All data processing was done in Matlab v7.2,(Mathworks, USA).

1) Target and Feature Extraction: Foot vertical clearance target points mx1 and MTC were extracted from Optotrak data using local maximum, minimum algorithms. (Fig .1). Three dimensional acceleration measurements obtained from IMU - accelerometer are respectively foot's acceleration along longitudinal axis (AccZ), medio-lateral axis (AccX), and anterior-posterior axis (AccY). Foot's rotation about anterior-posterior axis (GyroX) and medio-lateral axis (GyroY) are measured using gyroscopes in IMU. Peak AccZ features (F1, F2, and F3 in Fig. 3) during the toe-off event were extracted as they were the most correlated points with mx1 and MTC [9]. The corresponding features from the other sensor axes i.e.: AccX: features F4, F5, F6, AccY: features F7, F8, F9, Gyro X: features F10, F11, F12, GyroY: features F13, F14, F15, were extracted as well. This was done for each gait cycle.

2) Target Estimation using all sensor features: The objective was to build regression models that used input sen-

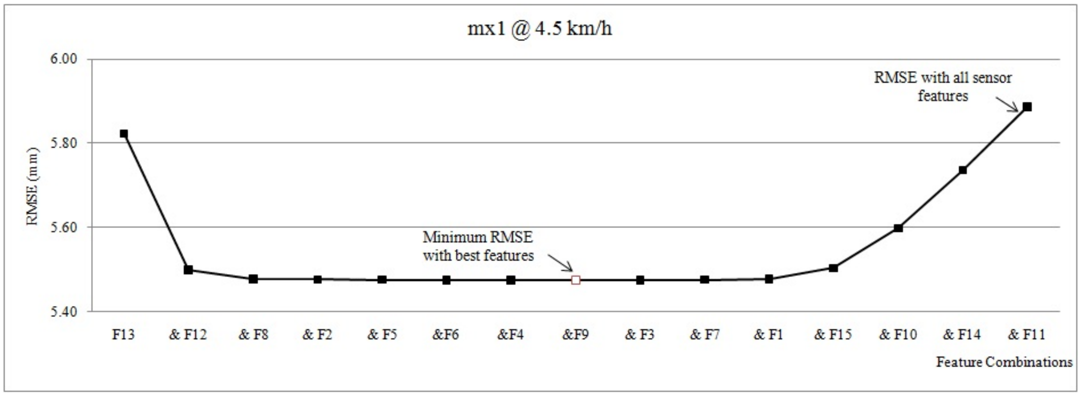

Fig. 4. Mx1 parameter estimation error at 4.5 km/h using Hill Climbing Feature Selection (s-parameter =100). The minimum RMSE is observed when the training features included F13, F12, F8, F2, F5, F6, F4, and F9

sor features to estimate mx1 and MTC. The Generalized Regression Neural Network (GRNN) consisting of a radial basis layer and a special linear layer [10] was used for this purpose. The estimated value $\hat{y}$ is obtained using the following equation where σ is the width of the radial basis function:

$$\hat{y} = \frac{\sum_{k=1}^{n} y_i e^{\frac{||x-x_i||^2}{2\sigma^2}}}{\sum_{k=1}^{n} e^{\frac{||x-x_i||^2}{2\sigma^2}}}.$$

The GRNN was implemented in Matlab which required the user to select the model parameter, (s). The spread s, is defined as the distance an input vector must be from the neuron weight vector to be 0.5. Initially, s was varied from 0.0001 to 100 and GRNN models were constructed with all input features (F1-F15). A leave-one-subject-out (LOSO) cross validation method was used to obtain the best GRNN model for each walking speed. In this method, data from one subject was used for testing while data from the remaining 7 subjects were used to train the model. This was done in turn for each subject. The lowest average LOSO RMSE was used to select the best GRNN model.

3) Hill Climbing Feature Selection: A hill-climbing feature selection method [11] was then applied to improve the estimation accuracy. The feature selection method began by computing the LOSO RMSE for a single individual feature using the best model parameters (i.e. spread) found in the previous section. The best feature (providing the lowest LOSO RMSE) was retained and the algorithm was executed to combine the remaining features in turn with this first feature. The second best feature in combination with the first was retained, and the algorithm proceeded in the same fashion until all features had been ranked and this was done for all walking speeds. The best set of features were the feature combination which produced the lowest LOSO RMSE. The percentage reduction in RMSE was calculated as:

$$Reduction\% = \frac{RMSE_{allfeatures} - RMSE_{bestfeatures}}{RMSE_{allfeatures}} \times 100\%.$$

III. RESULTS

Fig. 4 depicts an example of the hill climbing feature selection applied to estimate mx1 at 4.5 km/h (s-parameter = 100). Combination of features F13, F12, F8, F2, F5, F6, F4, and F9 produced the minimum RMSE error within all combinations.

Fig. 5 compares the average RMSEs across all subjects obtained with all sensor features and hill climbing feature selection at 2.5, 3.5, 4.5, and 5.5 km/h.

TABLE I tabulates the RMS estimation error obtained when the input parameters of the model included all the sensor features, the minimum RMSE when the input parameters were reduced based on hill climbing feature selection method, and the percentage reduction in RMSE for both mx1 and MTC at different speeds. At lower speeds hill climbing feature selection method reduced the RMSE by 6.75 - 21.93% and at highest speed the difference between the RMSE results obtained from all sensor feature estimation and hill climbing feature selection were very low (0.54% for mx1 and 2.59% for MTC).

IV. DISCUSSION

In this paper we applied GRNN to estimate two important foot end point clearances (mx1 and MTC) from raw inertial sensor data. The results suggest that both mx1 and MTC clearances can be accurately determined by the 3D foot kinematics during swing phase gait initialization.

The results indicated that both mx1 and MTC were better predictable at higher walking speeds (Fig. 5). This might be due to the decrease in parameter variability at higher walking speeds (for example at 2.5 km/h the mean range of mx1: 9.23-30.88 mm, maximum standard deviation (std): 0.57 mm whereas at 5.5 km/h mean range of mx1: 11.61-29.79 mm, maximum std: 0.38 mm). Higher walking speeds could be perceived by the locomotor system as risky, so the aim might be to reduce the foot clearance variability in order to improve safety

Overall the results indicated better prediction accuracies for mx1 clearances than MTC, which could be due to the fact that the mx1 event is closer to the toe-off features, and thus

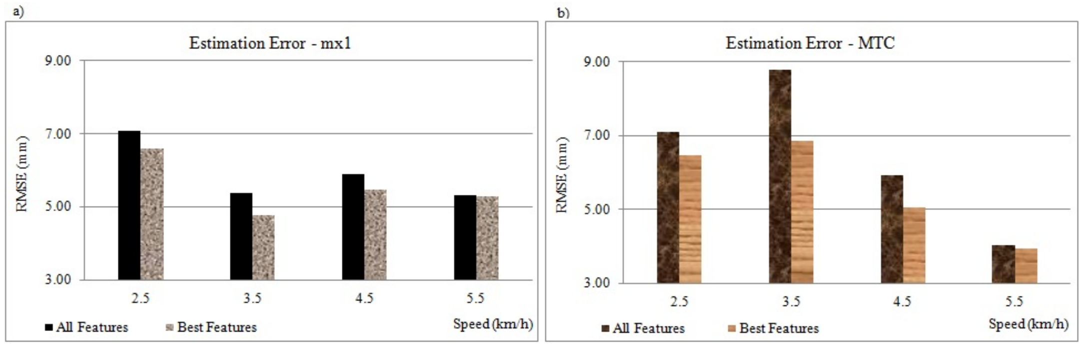

Fig. 5. Comparison of training errors obtained using all sensor features vs hill climbing feature selection method a) for mx1 and b) for MTC

Speed (km/h)	RMSE - mx1 (mm)		Reduction %	RMSE - MTC (mm)		Reduction %
	All Features	Best Features		All Features	Best Features	
2.5	7.08	6.61	6.75	7.09	6.47	8.77
3.5	5.38	4.77	11.47	8.78	6.86	21.93
4.5	5.89	5.48	7.00	5.92	4.95	16.43
5.5	5.32	5.30	0.54	4.04	3.93	2.60

TABLE I

RMS ESTIMATION ERRORS WITH ALL SENSOR INPUT FEATURES , WITH HILL CLIMBING FEATURE SELECTION, AND PERCENTAGE REDUCTION IN RMSE FOR MX1 AND MTC AT 2.5, 3.5, 4.5, AND 5.5 KM/H

might have greater influences. However, the application of feature selection offered better estimation performances for the MTC clearances compared to mx1 clearances (TABLE I), and this was more evident at lower walking speeds.

The optimal features consistently included F13, F12 and F2 for mx1 prediction (features F12 and F13 are linked to foot rotations about anterior-posterior axis and medio-lateral axis, whereas F2 is the maximum vertical acceleration of the foot). MTC best feature sets consistently contained F15, F9 and F2; suggesting that the maximum vertical acceleration at toe-off to be an important contributor to vertical foot trajectory clearances.

Further development of this regression model would incorporate various population groups such as healthy elderly, tripping fallers. This would avoid the biasness involved in selection of training data. After successful generalization, the model could be improved to predict the future gait events. This would facilitate rendering of bio-feedback to correct the risky gaits in clinical applications.

V. CONCLUSION

Machine learning techniques such as GRNN along with a feature selection algorithm have been shown to be a powerful tool to estimate the end point foot trajectory points using toe-off event inertial sensor data. The results are promising because the techniques require less computational overhead (toe-off event detection and three peak extractions) and can be implemented on chip for portable gait monitoring systems.

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