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Machine Learning Based Adaptive Gait Phase Estimation Using Inertial Measurement Sensors

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ABSTRACT

This paper presents a portable inertial measurement unit (IMU)-based motion sensing system and proposed an adaptive gait phase detection approach for non-steady state walking and multiple activities (walking, running, stair ascent, stair descent, squat) monitoring. The algorithm aims to overcome the limitation of existing gait detection methods that are time-domain thresholding based for steady-state motion and are not versatile to detect gait during different activities or different gait patterns of the same activity. The portable sensing suit is composed of three IMU sensors (wearable sensors for gait phase detection) and two footswitches (ground truth measurement and not needed for gait detection of the proposed algorithm). The acceleration, angular velocity, Euler angle, resultant acceleration, and resultant angular velocity from three IMUs are used as the input training data and the data of two footswitches used as the training label data (single support, double support, swing phase). Three methods 1) Logistic Regression (LR), 2) Random Forest Classifier (RF), and 3) Artificial Neural Network (NN) are used to build the gait phase detection models. The result shows our proposed gait phase detection with Random Forest Classifier can achieve 98.94% accuracy in walking, 98.45% in running, 99.15% in stair-ascent, 99.00% in stair-descent, and 99.63% in squatting. It demonstrates that our sensing suit can not only detect the gait status in any transient state but also generalize to multiple activities. Therefore, it can be implemented in real-time monitoring of human gait and control of assistive devices.

INTRODUCTION

In the last two decades, wearable devices, exoskeletons, and rehabilitation robots emerge as a new approach to prevent injuries and augment human capabilities [1]. In those applications, to determine the gait phase is crucial to monitor gait patterns, generate assistive torque profile, position profiles, and prevent injuries. Prior work studied foot switches [2], gyroscope [3], accelerometer [4], electromyography (EMG) [5] to detect gait cycles and used the information to trigger the assistance of wearable devices to augment the human walking. Typically, the movements of a limb in a gait cycle can be divided into 1) initial contact, 2) loading response, 3) mid-stance, 4) terminal stance, 5) pre-swing, 6) initial swing, 7) mid-swing, and 8) terminal swing [6]. Among those phases of the gait cycle, the most important events to separate the gait phase are heel-strike and toe-off [7]. Researchers have explored the foot pressure sensing system [8-10] and optical motion capture system [11-14] to obtain accurate gait cycle detection. Although these systems provide accurate gait detection, optical motion capture systems are heavy and not portable. Pappas et al. used the angular velocity of the foot and three force sensitive resistors to detect stance, heel-off, swing, and heel-strike in real-time and they achieve 99% accurate in climbing and walking in non-steady state walking and 96% for the subjects with impaired gait [10]. A foot pressure sensing system is not easily integrated into the wearable robots or may be unreliable due to its resistive sensing nature. Therefore, an IMU-based gait detection algorithm has been developed [15]. This algorithm uses the IMU sensor mounted on the foot and heuristic threshold to detect the heel-strike and toe-off event, then derive the gait cycle from 0 to 100% in time series with good accuracy in a steady state walking. But, if the subject suddenly changes their walking speed, stops walking, or changes activities, the gait cycle detection will become inaccurate.

The novelty of our algorithm overcomes the limitation of existing gait detection methods that are time-domain thresholding based for steady-state motion and are not versatile to detect gait during different activities or different gait patterns of the same activity. We developed a portable IMU-based motion sensing system and proposed a novel gait phase detection approach for non-steady state walking and multiple activities (walking, running, stair-ascent, stair-descent, squatting). The proposed approach not only detects the gait status in any transient state but also generalizes to multiple activities across different users without retraining the new user's data. Therefore, it can be implemented in real-time monitoring of human gait and control of assistive devices.

METHODS

In order to collect data to train the machine learning model, three IMUs and two footswitch insoles (B&L Engineering, USA) were deployed. IMUs were placed at back waist, left thigh front 3cm above the knee and left shank back 2cm above the ankle respectively, while insoles were worn on both feet and provided the pressure as the ground truth of the gait phase.

This study involved three healthy able-bodied subjects without (age = 29.3 ± 6.34 year; height = 1.75 ± 0.02 m; and weight = 86.3 ± 1.89 kg). The subjects were asked to wear the sensing suit and complete the following tasks:

- walking on the treadmill with speeds of 1.0, 1.5, 2.0, 2.5, 3.0, 3.5 and 4.0 miles/hour for 1 minute (each speed x1 time)
- running on the treadmill with a speed of 4.5 miles/hour for 1 minute (x1 time)
- climbing up and down 9 flights of stairs (x6 times)
- squatting 5 times (x4 times)

The sample rate is 200 Hz. The collected raw data needs to be processed to get features and labels which are used to feed the model. Besides the 3-axis Euler angle, acceleration and angular velocity signals from IMUs, the resultant acceleration, and angular velocity is calculated as additional signals. Features of each timestamp consist of the signals from three IMUs of the current timestamp and four previous timestamps. Based on the pressure of insoles, each timestamp gets a label among three phases including swing, single-support, and double-support.

The training set consists of data from two subjects, while the test set consists of data from the other subject. The training set of all tasks is fed to three machine learning models, including Logistic Regression (LR) [16], Random Forest Classifier (RF) [17] and Artificial Neural Network (NN) [18]. The LR model uses L2 penalty with the regularization parameter C=1; the RF model deploys 10 trees; and the NN model uses ReLU activation function and implements three hidden layers with 100, 50 and 25 neurons respectively. Then these models will be used to classify each timestamp of the test set into single-support phase, double-support phase or swing phase. This study used the accuracies calculated on every single task and the whole test set as a metric. Fig. 1 illustrates the flowchart of the algorithm.

RESULTS & DISCUSSIONS

The accuracy of each model on the whole test set is 90.22% for LR, 99.09% for RF, and 98.03% for NN respectively. The accuracies of models on different tasks are listed in Table 2. Figs. 2-6 illustrate the estimation results of each model.

As shown in Fig. 2, three models perform well on walking task, while LR model sometimes classifies single-support phase as a double-support phase. The wrong estimation usually behaves as a vibration between two phases, which could be solved easily by applying a filter. From Fig. 3, three models have similar performance on running and walking task for the transition from support phase to swing phase, while the reverse transition has a bad performance, which is because that running has only very short double support phase. The result shows that this IMU-based model could handle different pace speeds without loss of accuracy, indicating that it has the ability to deal with non-steady walking situations.

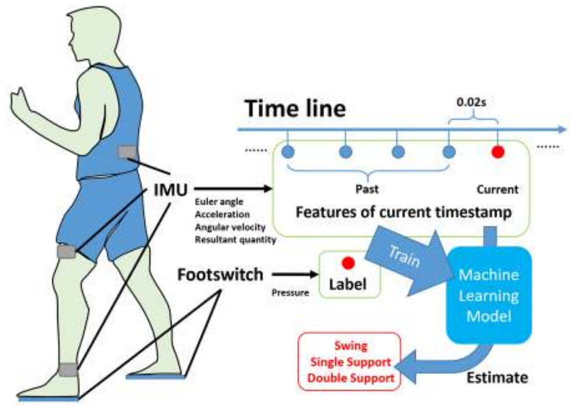

Fig. 1: System flowchart: IMU signals in combined with the calculated variables constitute the signals of one timestamp. Features of current timestamp are signals of current and four past timestamps. Current footswitch signal forms the label. Both features and labels are fed to the machine learning model.

	Walk	Run	Stair Ascent	Stair Descent	Squat
LR	94.43%	90.31%	85.90%	80.85%	80.19%
RF	98.94%	98.45%	99.15%	99.00%	99.63%
NN	98.36%	97.34%	97.28%	96.96%	98.27%

TABLE 2: Accuracy of Three Methods on Different Tasks

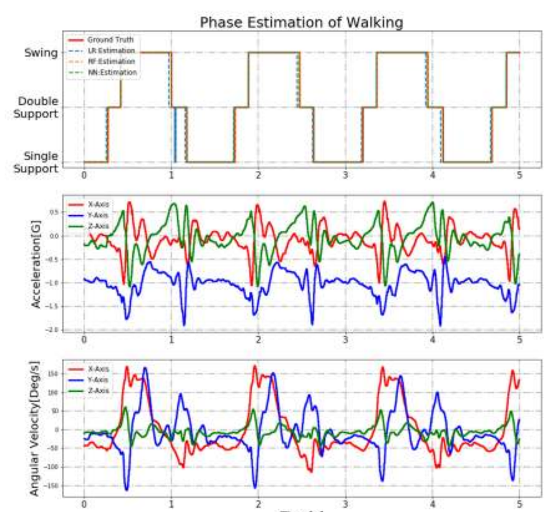

Fig. 2: Performance of three models on walking task. (Top) The ground truth and estimation of three models. (Middle) 3-axis acceleration during walking. (Bottom) 3-axis angular velocity during walking. LR model sometimes produces erroneous estimation while RF and NN perform very well.

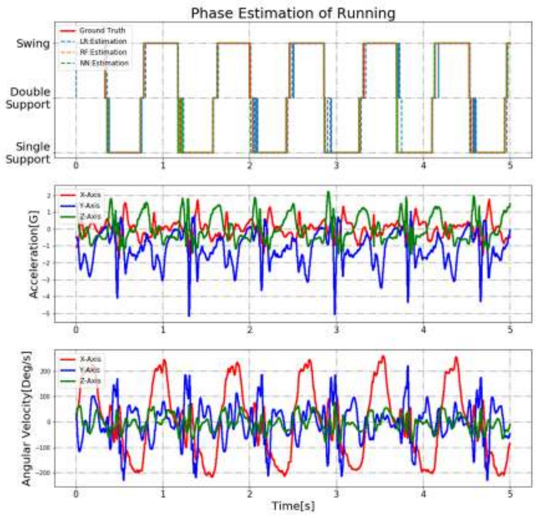

Fig. 3: Performance of three models on the running task. Three models give a similar performance of walking task on rising transition edge (from support phase to swing phase), while the reverse transition has bad performance. The lack of the double support phase in falling edge causes the model to produce erroneous estimation.

From Fig. 4 and 5, the LR model produces long time period erroneous estimation. This is because of the obvious difference between the gait behaviors of walking and stair-related tasks. It's challenging for a linear model to deal with this discrepancy due to its limited expression ability. NN model makes erroneous estimation near the phase transition point, which could also be solved by applying a filter. RF model still performs very well on stair-related tasks. Since the tasks with different gait behaviors are often mixed in real situations, models which only concentrate on a single task usually have limited usage. Our model shows its potentiality for handling mixed-tasks, which promises it a wider application prospect.

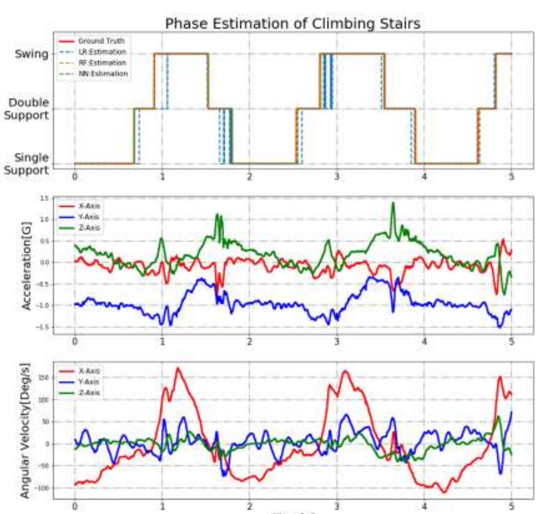

Fig. 4: Performance of three models on stair-ascent task. LR model takes longer time and produces erroneous estimation, while the other two models perform very well.

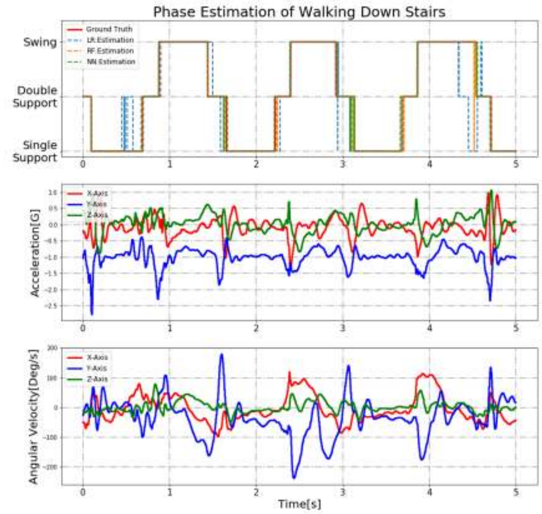

Fig. 5: Performance of three models on stair-descent task. Three models behave similarly with stair-ascent, while LR model makes even longer incorrect estimation.

On squatting task from Fig. 6, when misleading action is taken, the LR model will make the wrong estimation, while RF and NN models could still stick to the double-support phase. Combined with previous results about walking, running and stair-related tasks, our IMU-based models are functional in all kinds of tasks.

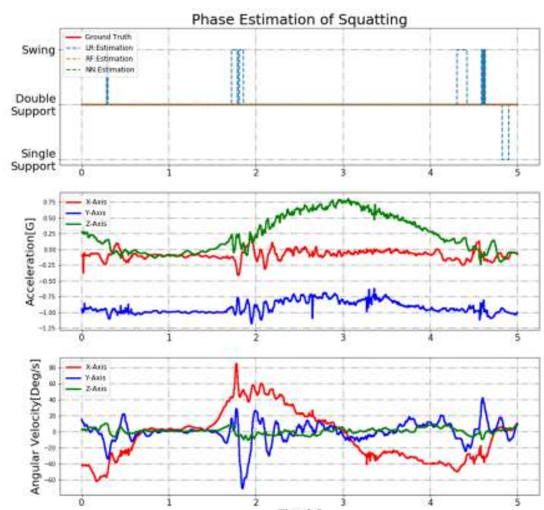

Fig. 6: Performance of three models on squatting task. RF and NN models resist the misleading action, while LR makes the wrong estimation.

CONCLUSIONS

From the above results, all three models were demonstrated to be functional in walking tasks, while RF and NN models have superior performance in all five tasks. As shown (Table 1), the proposed gait phase detection with the RF model achieves 98.94%, 98.45%, 99.15%, 99.00% and 99.63% accuracy in walking, running, stair-ascent, stair-descent and squatting task respectively. These results demonstrate that our IMU-based simple sensing algorithm can handle different pace speeds and different gait behaviors, which means that it's suitable for mixed-tasks, making it valuable for real-world mobility applications with real-world human activities which are typically non-steady-state and complicated. Besides, the latency of our algorithm is only related to the calculation ability without systematic delay, which means this method could provide a real-time estimation.

In addition, this model was used as a part of our knee-exoskeleton control system. The phase estimation from this algorithm was passed to the control system, and then the controller chose a dynamic function model corresponding to the gait phase to calculate the torque to deliver.

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