Detecting disorders in human walking behaviors using deep learning

Project Report

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Abstract:

In modern clinics, quantitative analyses are used to diagnose and treat gait pathology. Accordingly, foretasting walking kinematics and kinetics of people benefits to better understand gait patterns and construct assisting devices for rehabilitation. This capstone research proposes a deep learning algorithm (LSTM) for forecasting the walking kinematic of the knee in the Cartesian coordinate system. The hyper-parameter optimization using Gaussian Process method was used to predict walking kinematics of knee with an accuracy of 97%.

Contents

Chapter 1

Introduction

The capstone II is going to study the given topic from a different perspective compared to the capstone I, where tabular data was used to predict whether gait cycles of subjects are normal or abnormal. Presently in clinics, the evidence-based medicine works on the development of diagnosing and treating of pathologically disordered movements using quantitative analysis [17]. To be precise, the procedure of quantitative gait analysis involves measurements of joint kinetics and kinematics of the movement in three dimensions [3]. Attention is paid on determining deviations of pathological and asymptomatic populations from movement descriptive data. The gait of pathological populations is regularly recognized at their self-selected walking speed compared to asymptomatic populations [15]. A walking speed mismatch between pathological and asymptomatic populations can be observed by the spontaneous walking speed. For instance, stroke diagnosed people walk with the speed that ranges between 0.18 and 1.03 m/s, while asymptomatic populations speed that ranges between 1.04 and 1.60 m/s [16]. It should be emphasized that gait kinematics, kinetics spatiotemporal parameters, and muscular activity contribute walking speed [18].

Previous work

In [13], it is stated that motion and musculoskeletal forecasting is a powerful tool, and can be used for a variety of applications from designing assistive devices to testing theories of motor control. Here, the author made a prediction on quantitative data using bilevel optimization, where cost function was be determined from similar functions, representing an inverse optimal control problem [13]. The prediction of gait parameters related to foot-to-ground clearance during the walking provides an opportunity to see the risk tripping and falling risk in the older people [11], and can be realized with generalized regression neural network with errors 2–8%. Meanwhile, the paper [5] claims a modern context-aware motion prediction architecture, where the semantic-graph model was used with further implementation to the Recurrent neural networks. In [6], means of multivariate nonlinear time series prediction techniques are demonstrated, there is a possibility to increase the forecasting accuracy by taking into consideration movements of other people, with correlated mobility patterns as input data. Gait forecasting is not only for distinguishing normal and abnormal gait cycles, but it also benefits to better understand gait patterns of a wide range of populations [8], and will help to develop rehabilitation programs and gait performance [7].

The objective of this capstone research is an application of a deep learning algorithm, which is a long-short term memory that forecasts walking, kinematics of people. Moreover, the hyper-parameter optimization technique using the Gaussian Process is going to be implemented to achieve the high accuracy of the model. The study of bio-mechanical gait patterns of the knee joint is a promising diagnostic method of assessing injuries and pathology of it[1]. The knee joints allow movements with six degrees of freedom: three rotational components about the axes of a coordinate system and three translational components along this [1]. The Cartesian coordinate system is the reference system in bio-mechanics[10]. Therefore, the left and right knee movements of the subjects in the Cartesian system were chosen as a target value of walking kinematics data. For this research "A public dataset of overground and treadmill walking kinematics and kinetics in healthy individuals" was used [8].

Chapter 2

Methodology

2.1 Data

"A public dataset of overground and treadmill walking kinematics and kinetics in healthy individuals" was gathered by Fukuchi [8]. Data participants are 42 volunteers, including 24 young adults (age 27.6 ± 4.4 years, height 171.1 ± 10.5 cm, and mass 68.4 ± 12.2 kg) and 18 older adults (age 62.7 ± 8.0 years, height 161.8 ± 9.5 cm, and mass 66.9 ± 10.1 kg). All participants were free of any lower-extremity injury in the last six months before the data was collected, and all were free of any orthopedic or neurological disease. Kinetics and kinematics data of participants walking at different speeds were generated for the dataset both overground and on a treadmill. Participants were asked to walk with 8 different speeds on the treadmill, where trials were conducted from 40% to 145% of the self-selected, dimensionless speed. Not all older adults have walked at these 8 speeds. All mentioned information is available for each participant in metadata [8].

2.2 Data preprocessing

A treadmill dataset of walking kinematics of young individuals was extracted from the public dataset [8]. 24 subjects with 8 different speeds were considered, as a result, 192 trails were taken for this research. These 192 trials were randomized and were divided into train and test sets by 70 and 30% respectively. As kinematics data is time-series data, data points should be converted to supervised learning data, which means each current data point should hold the next data point as a target value. 26 data points were shifted upward used as target values of the current data point. As it was mentioned in the introduction, 6 attributes were used as target values such as the kinematics of the left and right knee in 3D dimensions. The neural networks work best on values roughly -1 and 1 [14], so the data should be scaled before using. Input (x) and target (y) values of the dataset were scaled independently because the target-data comes from the dataset of input values that is merely time-shifted so that target-data could be from a different source with different value-ranges. The following equation (equation 2.1) was used for scaling:

$$x = \frac{x - min(x)}{max(x) - min(x)}. \tag{2.1}$$

2.3 Deep learning algorithm

In this capstone research, Long short-term memory (LSTM) was used for forecasting walking kinematics of the knee. LSTM is an artificial recurrent neural network (RNN) architecture [9] used for sequential data type in deep learning [4].

2.3.1 Creating the LSTM

The Keras API was used as a framework.

- Sequential Model type was chosen.
- To the model was added LSTM layer with input shape of the number of input data attributes
- As an output a fully connected (or dense) layer was added because output signals should predict 6 attributes of target values. As an activation function sigmoid was used to squash an output to be between 0 and 1, which was scaled previously.
- To penalize a misclassified response value a mean square error was applied as the loss function. It should be mentioned that if the model only sees input-signals for a few time-steps, so its generated output may be significantly inaccurate [14]. The use of loss function at early time steps might cause the model to distort its later output. To pretend this issue a warm-up period of 50 time-step was used in calculating its accuracy in the loss function.
- An Root mean square prop (RMSProp) was used as an optimization algorithm.

Other details such as learning rate, number of dense layers, and nodes are going to be discussed in the next subsection 2.3.2.

2.3.2 Hyper-Parameter Optimization

Bayesian optimization is a sequential design process for finding global optimization of black-box functions [12]. However, the process of sequentially searching for the hyperparameters is expensive, therefore Bayesian optimization is going to be determined using the Gaussian process [2]. The optimizing function values are assumed to follow a multivariate gaussian. The covariance of the function values is provided by a Gaussian process kernel range of the parameters. Then a smart choice to choose the next parameter to evaluate can be made by the acquisition function over the Gaussian prior which accelerates the hyperparameter search [2].

In this capstone research, the following hyper-parameters are tuned by Bayesian optimization using Gaussian process:

- The learning-rate of the optimizer (ranged from 10^{-6} to 10^{-2}).
- The number of fully-connected or dense layers (between 0 and 5 layers).
- The number of nodes for each of the dense layers (from 2 to 512 nodes).
- Whether to use "sigmoid" or "relu" activation in dense layers.

A function "create model" was written in python by inputting mentioned hyper-parameter ranges, and those parameters were tuned by calling function gp_minimize from scikit-optimize library [2].

Chapter 3

Results and Discussion

Hyper - parameter optimization using Gaussian Process demonstrated the following results:

- learning-rate = 0.00020630710298876043 $\approx 2.1 * 10^{-4}$
- number of dense layers = 0
- number of nodes = 171
- activation function of dense layers is "sigmoid"

An unexpected result demonstrated a hyper parameter "dense layers", with the number of 0 layers. That means constructed model for forecasting seems quite simple. The detailed representation of hyper-parameter results can be seen from the figure A.1 in Appendix A. The red lines and points of the figure highlights the optimal hyper parameters.

All tuned hyper-parameters were used in LSTM model training, after, the model demonstrated 97% accuracy on the test dataset. As an example LSTM results for 40,000 data points can be seen from figure 3.1. As it can be found in plot labels, orange and blue lines demonstrate predicted and true values of target data.

For a detailed representation of results, figure 3.2 can be discussed, where all 6 target values (R - Right and L - Left knee in 3 axes) were demonstrated for 4000 data points. Actually, the LSTM illustrated quite high performance, in plots where vertical axis have labeled "R.KneeX" and "L.KneeX", true and predicted values are almost identical. However, the lowest two graphs of both knees of right and left 3.2 have some distortions. Meanwhile, vertically situated middle plots (R.KneeY and L.KneeY) are significantly similar despite the lowest points of the graphs. Moreover, it can be noticed the knee motion kinematics of the left leg is predicted with a little more accuracy compared to the right.

Generally, the LSTM showed its significant-high accuracy and predicted movement of Right and Left knee in all axis with quite acceptable results.

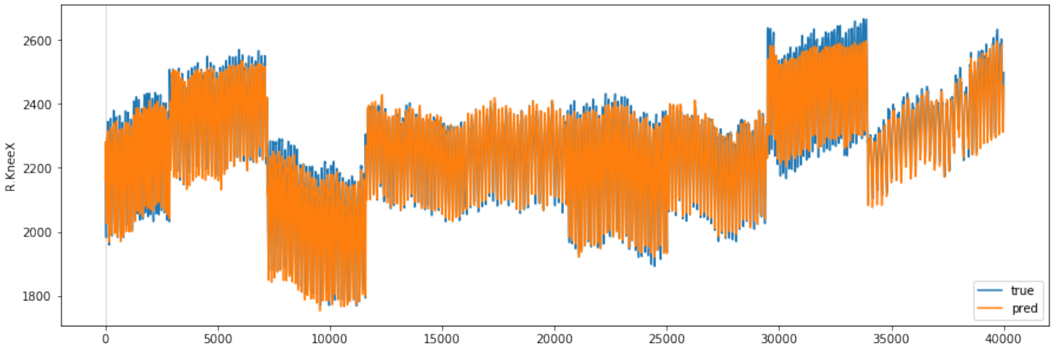

Figure 3.1: LSTM results for 40 000 data points for Right Knee in X-axis

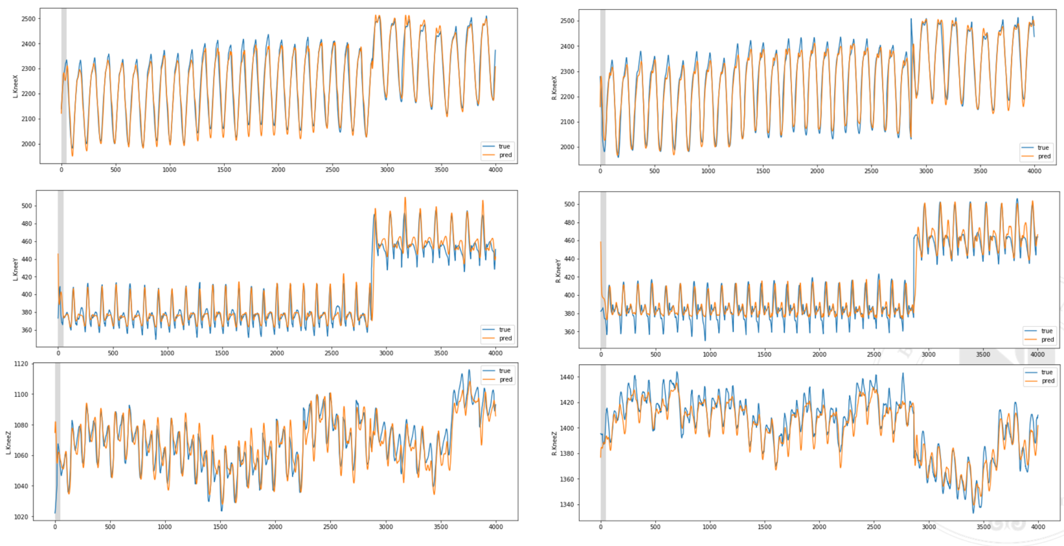

Figure 3.2: LSTM results for 4000 data points for left and right Knee in 3 axes

Chapter 4

Conclusion and Future work

In this capstone research, Hyper-Parameter optimization using Gaussian Process was completed, and these tuned parameters were applied in the LSTM model for forecasting the walking kinematics of people. The results were extensively analyzed, and suggest that the proposed model is able to predict walking kinematics of the left and right knee in a Cartesian coordinate system with high accuracy.

For future work, more features can be considered such as walking kinematics, spatiotemporal, demographic, and anthropometric parameters to better understand the waling speed of people [17]. Moreover, the walking speed kinematics prediction can be tested as biometric data in smart houses from camera data to detect whether a moving person is an owner or stranger.

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Appendix A

Hyper-Parameter Optimization results matrix

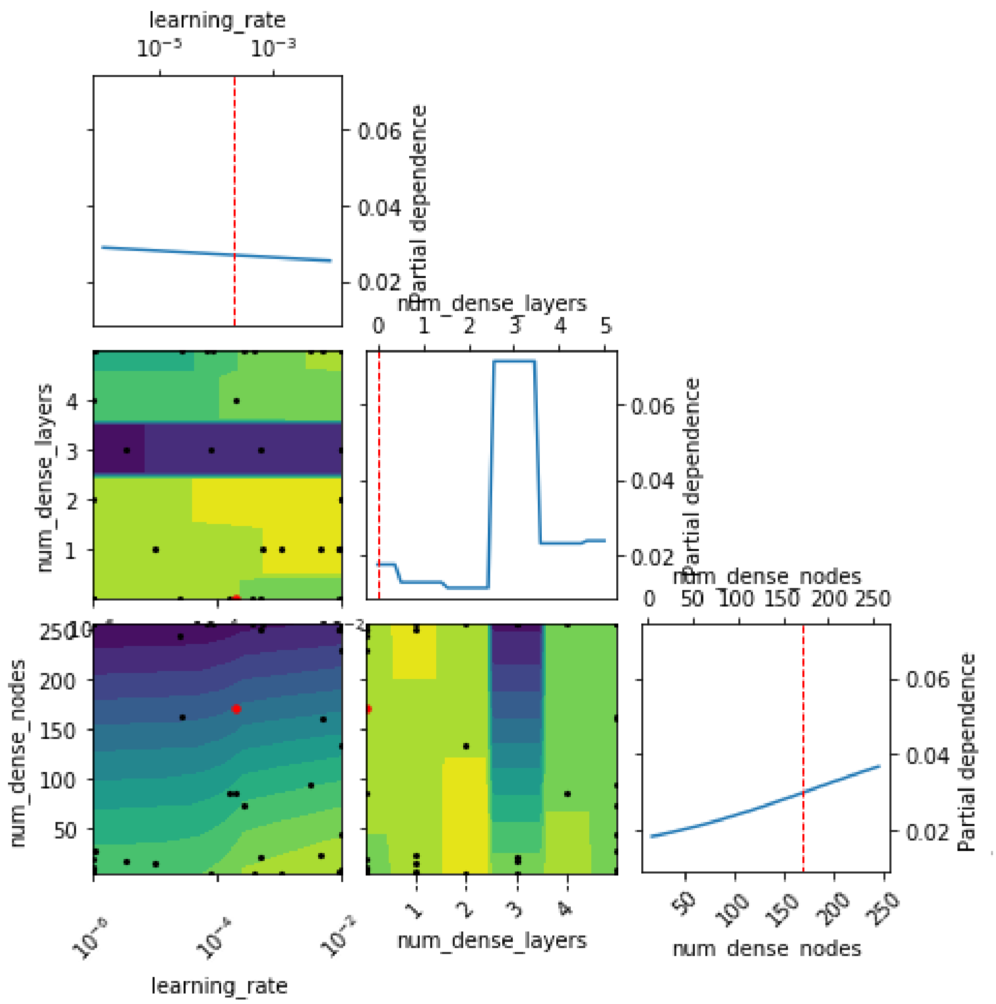

Figure A.1: Hyper-Parameter Optimization results matrix