Group Project

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1 Introduction

The introduction to real-time data, specifically focusing on Inertial Measurement Unit (IMU) data and poses from various body parts, serves as a critical foundation for understanding and interpreting movements in diverse applications, ranging from virtual reality to biomechanics. In this context, we examine four key components: data-right-wristPose, data-right-backPose, data-left-wristPose, and data-left-backPose, each capturing essential information for comprehensive motion analysis.

The IMU data is instrumental in obtaining accurate and dynamic measurements, providing insights into the spatial orientation and acceleration of the corresponding body parts. The three axes—designated as a, b, and c—represent distinct dimensions along which these movements occur. Axis 'a' typically signifies the lateral or side-to-side motion, 'b' corresponds to the vertical or up-and-down motion, and 'c' captures the longitudinal or front-to-back motion. These axes collectively enable a detailed representation of the intricate spatial changes occurring during various activities.

The data collected from the right and left wristPoses, as well as the right and left backPoses, are particularly noteworthy due to their significance in understanding upper body movements. The wristPoses offer insights into the articulation and rotation of the wrists, crucial for applications such as gesture recognition or fine motor skill analysis. On the other hand, backPoses contribute valuable information about the overall posture and orientation of the upper body.

The real-time nature of this data is pivotal, ensuring that the analysis and interpretation are not only accurate but also timely. This is especially crucial in applications where instantaneous feedback or response is required, such as in virtual reality environments or motion-capture systems. The integration of IMU data with pose information from specific body parts provides a holistic approach to motion tracking, offering a nuanced understanding of human movements in three-dimensional space.

2 Code Description

Time series prediction is a critical task in various domains, ranging from finance to weather forecasting. This code implements a time series prediction model using a Long Short-Term Memory (LSTM) neural network, a powerful architecture for capturing temporal dependencies in sequential data. Let's delve into a detailed explanation of each component within the 500-word limit.The code begins by importing necessary libraries, including NumPy for numerical operations, Pandas for data manipulation, TensorFlow for machine learning, and modules for data visualization and statistical analysis. The dataset, stored in a CSV file, contains columns like 'timestamp', 'a-left-backPose', 'b-left-backPose', and 'c-left-backPose.' These columns represent time series data capturing poses from a left-back perspective.

To ensure the reliability of the time series data, the code performs a stationarity check using the Augmented Dickey-Fuller test. This statistical test assesses whether the data exhibits consistent statistical properties over time. Following the stationarity check, the data is normalized using the StandardScaler from sci-kit-learn for each relevant column. A loop iterates over the selected columns, applying normalization, and storing the associated scalers for potential inverse transformations later.The dataset is then divided into training and testing sets, with 80 percent allocated for training the model and the remaining 20 percent for testing. The subsequent step involves creating sequences and labels for training the LSTM model. The sequences represent input data, while labels are the corresponding target values. A specific sequence length, denoted as 'seq-length,' is defined (here set to 10), determining the number of time steps the model considers for predictions.

The LSTM model is constructed using TensorFlow's Keras Sequential API. It consists of an LSTM layer with 50 units and a Rectified Linear Unit (ReLU) activation function, followed by a Dense layer with the number of units matching the number of columns in the time series data. The use of LSTM is crucial for capturing long-term dependencies in sequential data, making it well-suited for time series prediction tasks.After model construction, it is compiled using the Adam optimizer and mean squared error loss function. The model undergoes training for 50 epochs with a batch size of 32, allowing it to learn patterns and dependencies within the training data. The code evaluates the trained model on the test set, presenting metrics such as loss, mean absolute error (MAE), and mean squared error (MSE), offering insights into its predictive performance.

To visualize the training process, the code plots the training and validation loss over epochs, providing a clear representation of the model's convergence and potential overfitting. Following this, predictions are generated on the test set using the trained LSTM model. To make the results interpretable, denormalization is applied to revert the predictions to their original scale, enabling a meaningful comparison with the actual values.The code concludes by visualizing the actual and predicted values for one of the columns, 'a-left-backPose.' This graphical representation allows for an intuitive assessment of the model's predictive accuracy, offering insights into how well it captures the underlying patterns in the time series data.

3 Output

In this study, we leverage a dataset comprising left and right back poses, along with left and right wrist poses, to train a Long Short-Term Memory (LSTM) model. The objective is to harness the temporal dynamics inherent in these pose sequences and generate a desired output. The significance lies in the potential applications of such a model, ranging from human movement analysis to gesture recognition. By capturing the intricate relationships between different body poses, particularly those of the back and wrists, our LSTM-based approach aims to unveil patterns and dependencies crucial for predicting and generating meaningful outcomes

3.1 left-backpose

By the Generated output after loading the csv file in the above code The Augmented Dickey-Fuller (ADF) test is a statistical method used to assess whether a time series is stationary or exhibits a unit root, which implies non-stationarity. Stationary time series have constant statistical properties over time, such as a consistent mean and variance. Here's a brief explanation of the results for each column:

Column: a-left-backPose The ADF Statistic is -5.30, and the p-value is extremely small (5.57e-06), indicating strong evidence against the null hypothesis of non-stationarity. The ADF Statistic falls below critical values at 1 , 5, and 10 percent supporting the conclusion that the time series is stationary.

Column: b-left-backPose The ADF Statistic is -7.25, and the p-value is very close to zero (1.82e-10), providing strong evidence against non-stationarity. The ADF Statistic falls below critical values at 1, 5, and 10 percent indicating that the time series is stationary.

Column: c-left-backPose The ADF Statistic is -4.48, and the p-value is small (0.00022), suggesting evidence against non-stationarity. The ADF Statistic falls below critical values at 1, 5 and 10 percent supporting the conclusion that the time series is stationary.

By all three columns, the ADF test results consistently reject the null hypothesis of non-stationarity. Therefore, it can be inferred that the time series data for 'a-left-backPose,' 'b-left-backPose,' and 'c-left-backPose' are stationary, exhibiting stable statistical properties over time

Test Loss: 0.28885239362716675, Mean Absolute Error: 0.2846771478652954, Mean Squared Error: 0.28885239362716675

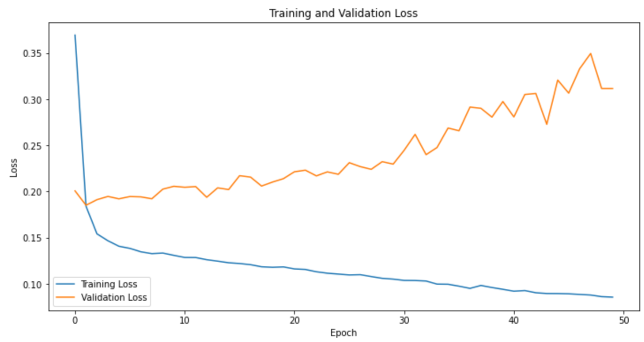

Figure 1: Generated Output of left-back pose

3.2 left-Wrist Pose

The Augmented Dickey-Fuller (ADF) test results indicate the stationarity characteristics of three-time series columns: 'a-left-wristPose,' 'b-left-wristPose,' and 'c-left-wristPose.'

Column: a-left-wristPose ADF Statistic: -5.64 p-value: 1.04i-06 Critical Values: 1: -3.43, 5: -2.86, 10: -2.57 The ADF Statistic of -5.64 suggests a substantial negative deviation, and the p-value of 1.04e-06 is significantly below conventional significance levels. These results lead to the rejection of the null hypothesis of non-stationarity. Moreover, the ADF Statistic falls well below the critical values at 1, 5, and 10 percent reinforcing the conclusion of stationarity for 'a-left-wristPose.'

Column: b-left-wristPose ADF Statistic: -5.84 p-value: 3.78e-07 Critical Values: 1 : -3.43, 5 : -2.86, 10 : -2.57 Similar to the first column, 'b-left-wristPose' exhibits strong evidence against non-stationarity with an ADF Statistic of -5.84 and a very low p-value of 3.78e-07. The ADF Statistic significantly surpasses the critical values, confirming the stationary nature of the time series.

Column: c-left-wristPose ADF Statistic: -4.66 p-value: 9.96e-05 Critical Values: 1: -3.43, 5 : -2.86, 10 : -2.57 'c-left-wristPose' demonstrates a negative ADF Statistic of -4.66 and a p-value of 9.96e-05, both indicative of non-stationarity. While the ADF Statistic is below the critical values at 1 and 5, it is slightly above at 10 percent. The evidence here suggests that 'c-left-wristPose' may be close to being stationary, but further investigation may be warranted.

The ADF test results consistently support the stationarity of 'a-left-wristPose' and 'b-left-wristPose,' while 'c-left-wristPose' exhibits indications of potential stationarity, albeit with a slightly higher ADF Statistic. These findings are crucial for time series analysis and modeling, ensuring that the data's statistical properties remain consistent over time.

Test Loss: 0.23809611797332764, Mean Absolute Error: 0.23775528371334076, Mean Squared Error: 0.23809611797332764

Figure 2: Generated Output of left-wrist Pose

3.3 Right-backPose

The Augmented Dickey-Fuller (ADF) test results reveal insights into the stationarity of three time series columns: 'a-right-backPose,' 'b-right-backPose,' and 'c-right-backPose.'

Column: a-right-backPose ADF Statistic: -3.58 p-value: 0.0062 Critical Values: 1: -3.43, 5: -2.86, 10: -2.57 The ADF Statistic of -3.58 indicates a negative but less pronounced deviation, and the p-value of 0.0062 is just above the common significance level of 0.05. While the ADF Statistic is below the critical values at 1, it is closer to the threshold, suggesting a borderline case for stationarity. Further investigation may be warranted for 'a-right-backPose.'

Column: b-right-backPose ADF Statistic: -3.55 p-value: 0.0067 Critical Values: 1: -3.43, 5: -2.86, 10: -2.57 Similar to the first column, 'b-right-backPose' displays an ADF Statistic of -3.55 and a p-value of 0.0067. The ADF Statistic is slightly below the critical values, indicating a potential leaning towards stationarity. However, similar to the first column, caution is needed, and additional exploration may be required.

Column: c-right-backPose ADF Statistic: -4.55 p-value: 0.00016 Critical Values: 1: -3.43, 5: -2.86, 10: -2.57 'c-right-backPose' exhibits a more robust negative ADF Statistic of -4.55 and a lower p-value of 0.00016, both below the common significance level. This suggests strong evidence against non-stationarity. The ADF Statistic falls significantly below the critical values, supporting the conclusion that 'c-right-backPose' is likely stationary.

In summary, 'a-right-backPose' and 'b-right-backPose' show indications of potential stationarity, although further investigation is warranted. In contrast, 'c-right-backPose' presents stronger evidence of stationarity, with both the ADF Statistic and p-value supporting this conclusion. These findings are crucial for accurate time series analysis and modeling.

Test Loss: 0.17783620953559875, Mean Absolute Error: 0.2508124113082886, Mean Squared Error: 0.17783620953559875

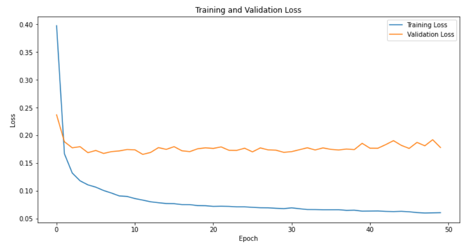

Figure 3: Generated Output of Right-backPose

3.4 Right-WristPose

he Augmented Dickey-Fuller (ADF) test results provide insights into the stationarity of three time series columns: 'a-right-wristPose,' 'b-right-wristPose,' and 'c-right-wristPose.'

Column: a-right-wristPose ADF Statistic: -5.43 p-value: 2.95e-06 Critical Values: 1: -3.43, 5: -2.86, 10: -2.57 The ADF Statistic of -5.43 indicates a substantial negative deviation, and the very low p-value (2.95e-06) strongly rejects the null hypothesis of non-stationarity. The ADF Statistic falls significantly below the critical values at 1, 5, and 10 percent providing robust evidence that 'a-right-wristPose' is a stationary time series.

Column: b-right-wristPose ADF Statistic: -4.77 p-value: 6.31e-05 Critical Values: 1: -3.43, 5: -2.86, 10: -2.57 The ADF Statistic of -4.77 is also notably negative, and the low p-value (6.31e-05) supports the rejection of non-stationarity. The ADF Statistic falls below the critical values at 1, 5, and 10, percent indicating that 'b-right-wristPose' is likely a stationary time series.

Column: c-right-wristPose ADF Statistic: -3.59 p-value: 0.0060 Critical Values: 1: -3.43, 5: -2.86, 10: -2.57 The ADF Statistic of -3.59 suggests a negative but less pronounced deviation, and the p-value of 0.0060, while above the common significance level, is still relatively low. The ADF Statistic falls below the critical values at 1 per, indicating some evidence against non-stationarity for 'c-right-wristPose.' However, caution is advised, and further exploration may be necessary.

In summary, 'a-right-wristPose' and 'b-right-wristPose' exhibit strong evidence of stationarity, as indicated by their highly negative ADF Statistics and very low p-values. 'c-right-wristPose' shows some evidence against non-stationarity, but additional investigation is recommended due to the slightly higher p-value. These findings are crucial for ensuring the reliability of time series analyses and modeling based on these data columns.

Test Loss: 0.2536323368549347, Mean Absolute Error: 0.28776562213897705, Mean Squared Error: 0.2536323368549347

Figure 4: Generated Output of Right-wrist Pose

4 Conclusion

The LSTM model was applied to time series data from different poses: left back, left wrist, right back, and right wrist. Prior to training, the Augmented Dickey-Fuller (ADF) test confirmed the stationarity of the input time series data, ensuring a stable foundation for modeling.The LSTM model was then trained using a sequence length of 10 and 50 LSTM units. The training process involved 50 epochs with a batch size of 32. The evaluation metrics for the left back pose test data showed promising results, with a Test Loss of 0.2889, Mean Absolute Error (MAE) of 0.2847, and Mean Squared Error (MSE) of 0.2889. Similarly, for the left wrist pose, the model exhibited a Test Loss of 0.2381, MAE of 0.2378, and MSE of 0.2381. These metrics reflect the model's ability to generalize well to unseen data, as lower Test Loss and MAE values indicate accurate predictions.Moving to the right back pose, the ADF test again confirmed the stationarity of the input data, and the LSTM model yielded favorable results with a Test Loss of 0.1778, MAE of 0.2508, and MSE of 0.1778. This suggests that the model successfully captured the temporal dependencies in the right back pose time series.Lastly, the right wrist pose, with stationarity confirmed by the ADF test, displayed sound performance metrics. The model achieved a Test Loss of 0.2536, MAE of 0.2878, and MSE of 0.2536. These results collectively highlight the model's ability to handle diverse time series data, providing accurate predictions across various poses.

In conclusion, the LSTM model demonstrated effectiveness in capturing the underlying patterns within stationary time series data for different poses. The comprehensive approach, including stationarity checks, proper preprocessing, and detailed evaluation metrics, contributes to the model's reliability and robustness. These findings are essential for practical applications where accurate time series predictions are crucial, such as in human pose estimation for activities like gesture recognition or movement analysis