IMPROVING DISPLACEMENT ESTIMATION BY MEMS ACCELEROMETER USING DEEP Q-LEARNING ALGORITHM

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Introduction

Precise estimation of movement trajectories using cheap MEMS accelerometers could have a wide range of applications, such as simplified industrial robot control, drone navigation, etc. Cheap accelerometers, however, have significant measurement errors. These compound to extremely large deviations when calculating displacements which result in estimated trajectories becoming completely different from the ones the sensor travelled along. Traditional filtering techniques ranging from simple threshold filter to more complex Kalman filter can be used to improve the measurement accuracy with varying levels of success. For this application, however, these filters either make the whole system insensitive or require dedicated tuning of filter parameters for each trajectory measurement case.

Applying machine learning (ML) algorithms for improving both accuracy and consistency of trajectories estimated based on accelerometer data is a promising area of research. There already are studies confirming that both LSTM-based ML algorithm [1] and ML-Kalman filter combinations [2, 3] offer improved performance compared to traditional filtering methods. To supplement that research, this work explores the application of deep q-learning algorithm to improve displacement accuracy evaluation based on accelerometer data.

Methodology

The studied method involves training the algorithm on ideal displacement data and the displacement datasets that were calculated from raw acceleration data. The raw acceleration dataset for the algorithm training was collected using a combination of MPU6050 accelerometer and ESP32 microcontroller. To obtain precise and repeatable trajectories, the sensor was mounted on the end-effector of a Motoman SSF2000 articulated robot.

Every iteration, the neural network of the deep q-learning algorithm is fed data from the previous iteration that countains information about how well the corrected displacement matched the ideal case. The reward function for the q-learning part determines the reward by comparing deviation obtained on current iteration compared to the one from the last iteration. The algorithm then outputs corrected displacement value for the next iteration. To smooth out the displacement curve, approximating filter is applied.

The algorithm for accelerometer data collection and training of the deep q-learning algorithm is visualized in Fig. 1. The first part describes recording of data while the accelerometer is moved along a known, pre-determined trajectory. After the data is collected, the deep q-learning algorithm is trained as previously described.

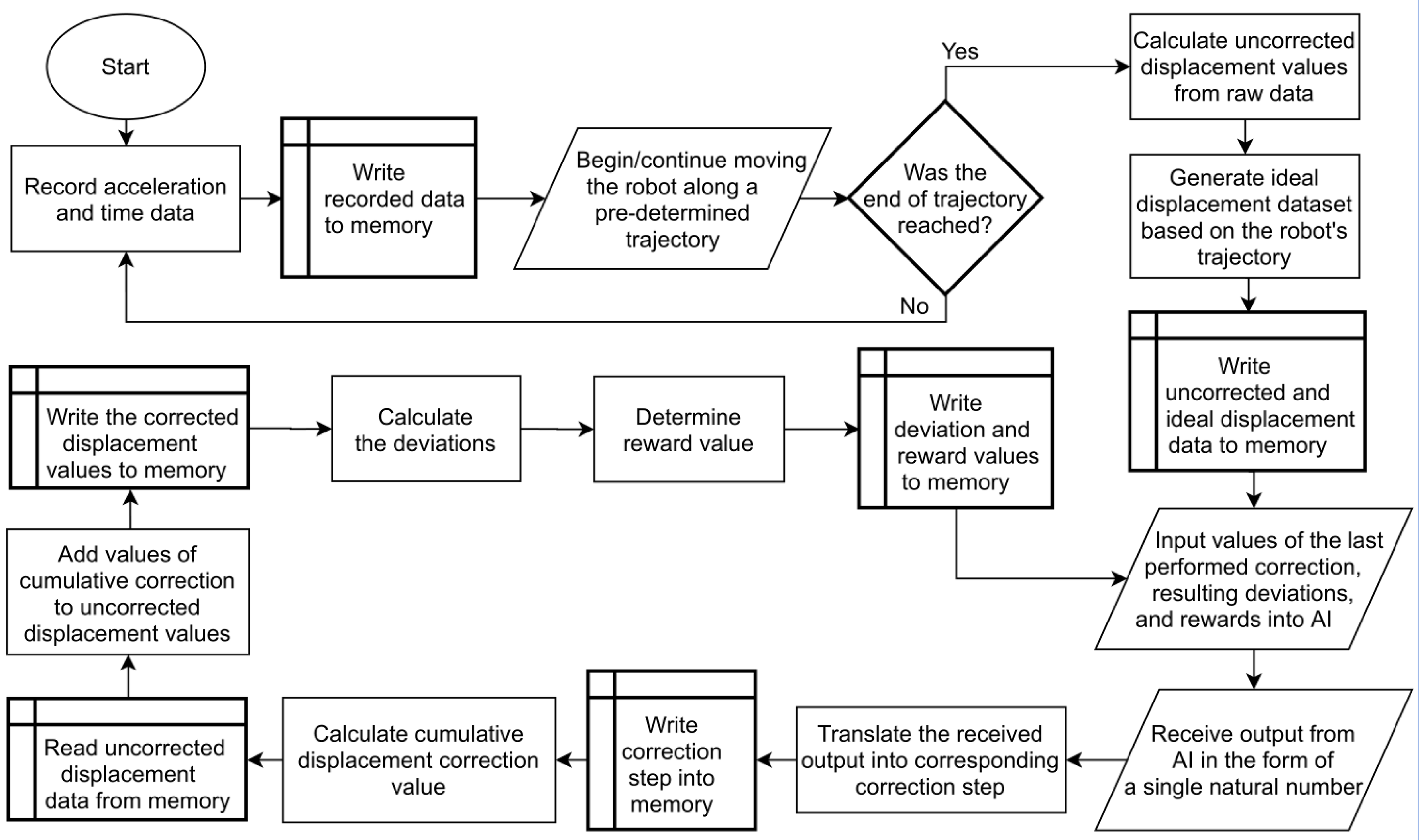

Fig. 1. Data collection and ML training algorithm.

Results and discussion

One of preliminary results of this research is given in Fig. 2, which shows displacement curves of moving a MPU6050 accelerometer in a straight line along one axis at constant velocity (apart from initial acceleration and the final deceleration) for 0.4 m. distance. The sampling frequency was set to 50 Hz.

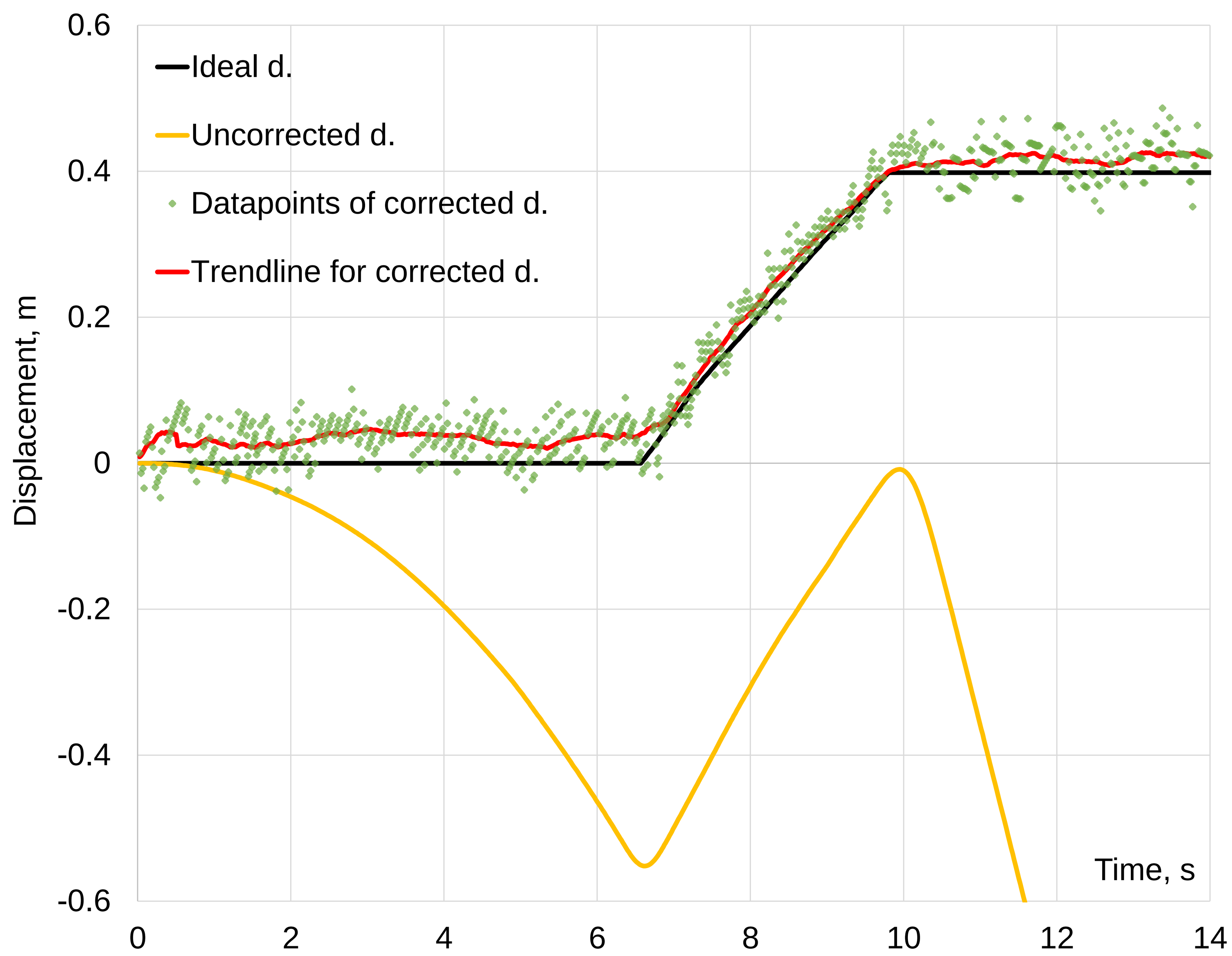

Fig. 2. Comparison of uncorrected and corrected displacements to the ideal displacement case.

There is a complete mismatch between the uncorrected displacement (calculated from raw acceleration data) and the one that was performed in reality (ideal case). Meanwhile, the displacement corrected by a deep q-learning algorithm and then passed through an averaging filter (shown as trendline in Fig. 2) matches the ideal case closely. The average deviation from the ideal case is around 5%, while maximum deviation is around 18%, which is a significant accuracy improvement for such type of accelerometer.

Conclusions

The obtained accuracy of the correcting algorithm significant and can even be comparable to the other ML-based correction techniques. However, further research is required to make the technique applicable in practice: the algorithm needs to be made less reliant on ideal displacement data, while its performance for motion in complex trajectories needs to be investigated.

References

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