

Demo: Dynamic Time Warping as a Tool for Comparing CAN data

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Abstract—CAN bus traces from repeated dynamic events often do not align. Dynamic Time Warping (DTW) is a tool used to efficiently align traces by time. For this demo, multiple CAN bus traces were taken from the same vehicle performing the same maneuvers. By using DTW, the similarity of the traces was able to be quantified. Specifically, CAN bus traces were compared from a heavy truck performing the same test sequence. DTW distance score showed 661 compared to the direct Euclidean distance score of 24032; this shows that utilizing DTW can accommodate differences in time during comparison of CAN traces. DTW techniques help improve pattern matching for similar driving behaviors.

I. DEMONSTRATION

When comparing two similar data traces the Euclidean distance, found using the square root of the Sum of Squares method, is typically used by software tools to measure the difference between the two aligned traces. The distance score is a nondimensional normalized value of the traces being compared. However, if the time difference of the two traces is too different, understanding the value of the Euclidean distance measurement becomes challenging, and a conclusion becomes hard to draw. Dynamic Time Warping (DTW) is an algorithm developed to compare two similar data signals of different temporal lengths by warping the time axis [1]. Applying DTW to the two traces can then remove that time error, allowing the software to accurately report distance. Furthermore, DTW may provide a tool for comparative analysis for driving behavior to detect anomalies.

In the heavy vehicle domain, CAN data is frequently recorded during on-road testing. However, that data is subject to random events such as red lights and traffic density changing between cycles. These events then change the time length of the dataset, which directly affects the comparison. DTW can be used to align these traces to accurately reflect the route cycle driving distance.

To generate the required CAN bus traces, a Cummins powered heavy duty truck was utilized. The cycle consisted of an idle phase, acceleration phase to approximately 15 mph, followed by a hard brake event to an idle phase.

Once traces were generated, they were compared using code written in Python. The traces were first overlaid over each other for visual comparison and direct Euclidean distance

Cummins Heavy Truck Engine Speed: Pre-Alignment and DTW Application

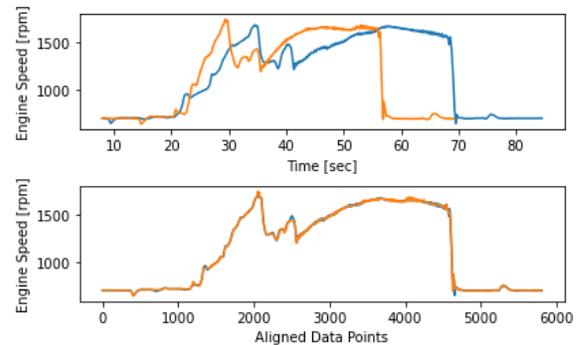


Fig. 1. Engine speed traces for Cycles A and B, showing pre-alignment (top) and after application of DTW (bottom).

TABLE I
EUCLIDEAN AND DTW DISTANCE OF CYCLES A AND B

| Comparison | Euclidean Distance | DTW |
|--------------------|--------------------|----------|
| A vs B | 24032.986 | 661.534 |
| A vs A, deletion | 6170.097 | 194.574 |
| A vs A, alteration | 5583.231 | 6700.396 |

measurements, shown in Figure 1, top. Next, the same two traces were compared using the DTWAlign Python package [2], shown in Figure 1, bottom. The Euclidean and DTW distance scores are recorded in Table I.

The data from Cycle A was then altered and compared to the base data. First, one second of engine speed data was completely removed. The Euclidean distance increased by 6170, showing that data deletion was recognized. DTW aligned the data regardless of the deletion and had a score of approximately 195. This means that a small amount of missing data does not affect the algorithm. Next, one second of engine speed data was altered to 300 rpm. The Euclidean distance changed by 5583, while the DTW distance changed by 6700. DTW is a useful tool for dealing with data sets from CAN that have variable time bases. Potential applications include anomaly detection once driving patterns are established or routes are known through location services. General comparison of CAN traces can be enhanced through DTW.

REFERENCES

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- [2] Suzuki, T. (2019). STATEFB/DTWALIGN: Comprehensive Dynamic Time Warping Module for Python. GitHub. Retrieved January 3, 2022, from <https://github.com/statefb/dtwalign>