ETH zürich

Schweizer Paraplegiker Zentrum

Schweizer Paraplegiker Forschung

CAI LAB

Biosignal Synchronization Across Devices In Robotics Application

Semester Project

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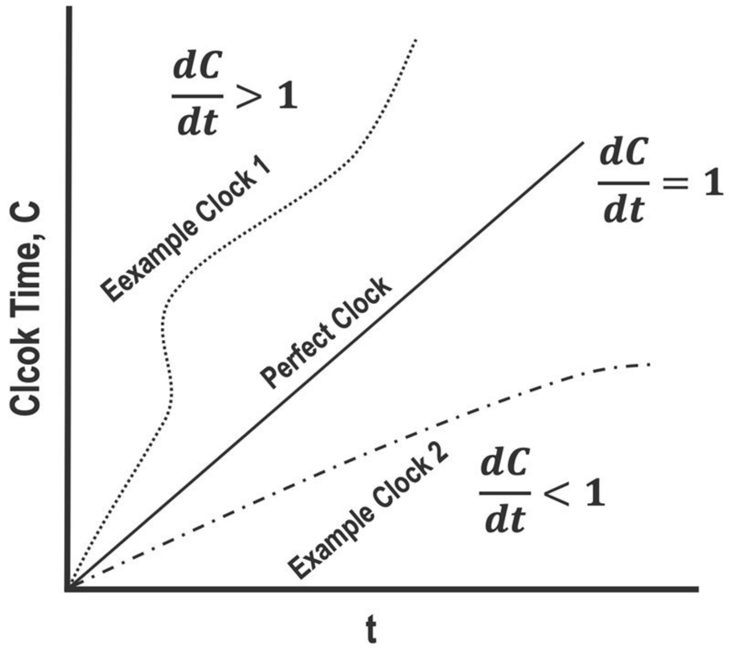
ETH Zürich, Switzerland | 05 December 2024

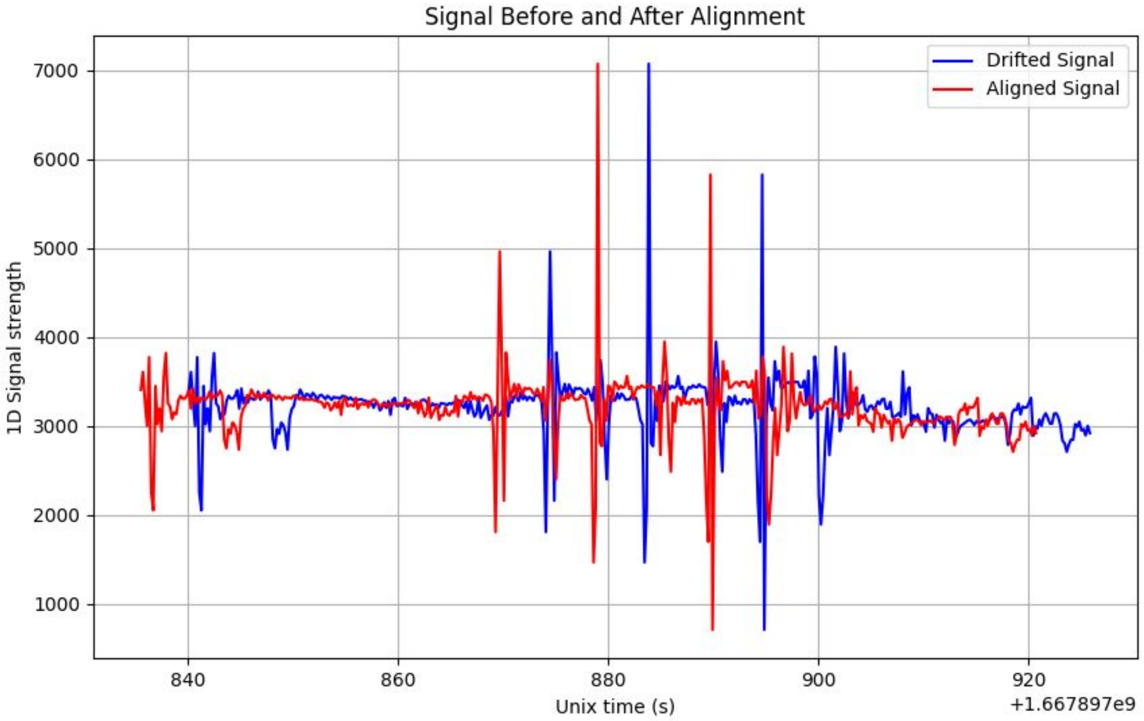
Problem Definition

- Sensor data has clock drift
  - estimate: up to 4 seconds drift per day (worst case)

  → Disadvantageous for classification task



Schütz et al. (2021), "Deep Canonical Correlation Alignment”

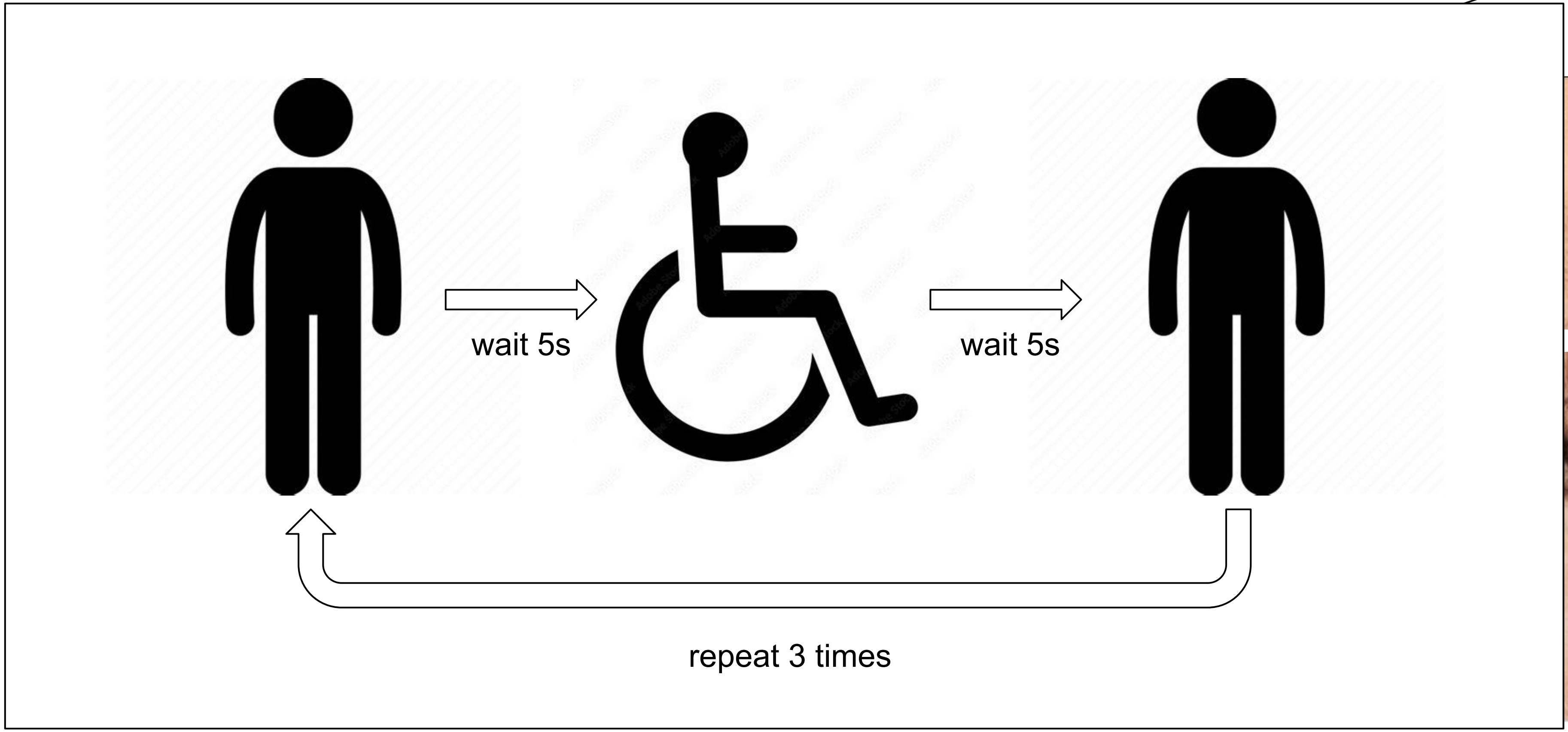


Dataset

- SCAI-SENSEI-V2
  - 20 user recordings, ~45 min each
  - Includes extrinsic (synching) events at start & end
- Sensors:
  - Corsano (**Accelerometer**, Temperature, RR interval, etc), 32 Hz
  - Cosinuss (**Accelerometer**, Heart Rate, PPG, etc), 100 Hz
  - VivaLink (**Accelerometer**, ECG, Heart Rate, etc), 5 Hz
  - Sensomative (**Pressure Mat**), 10 Hz
  - and more

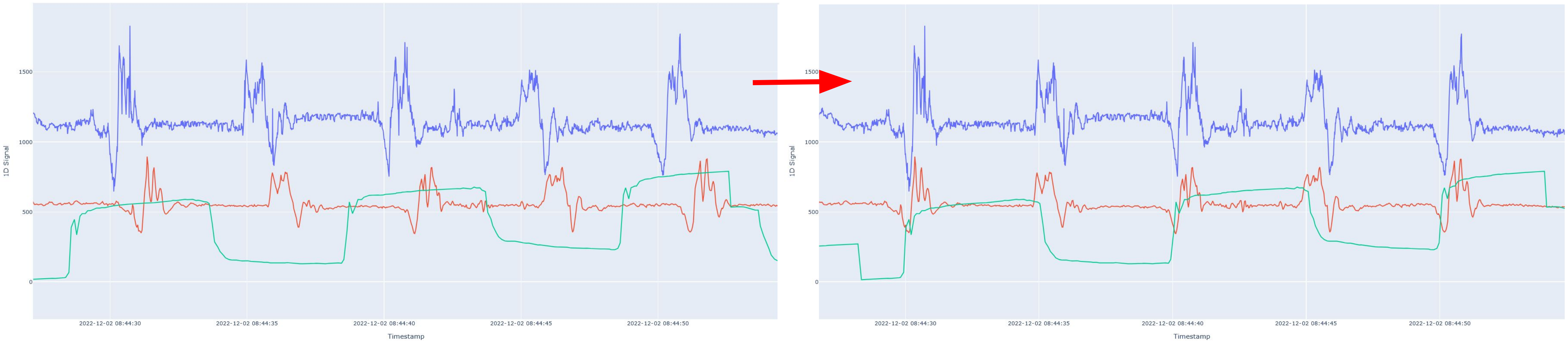
Dataset

- SCAI-SENSEI-V2
  - 20 user recordings, ~45 min each
  - Includes extrinsic (synching) events at start & end
-

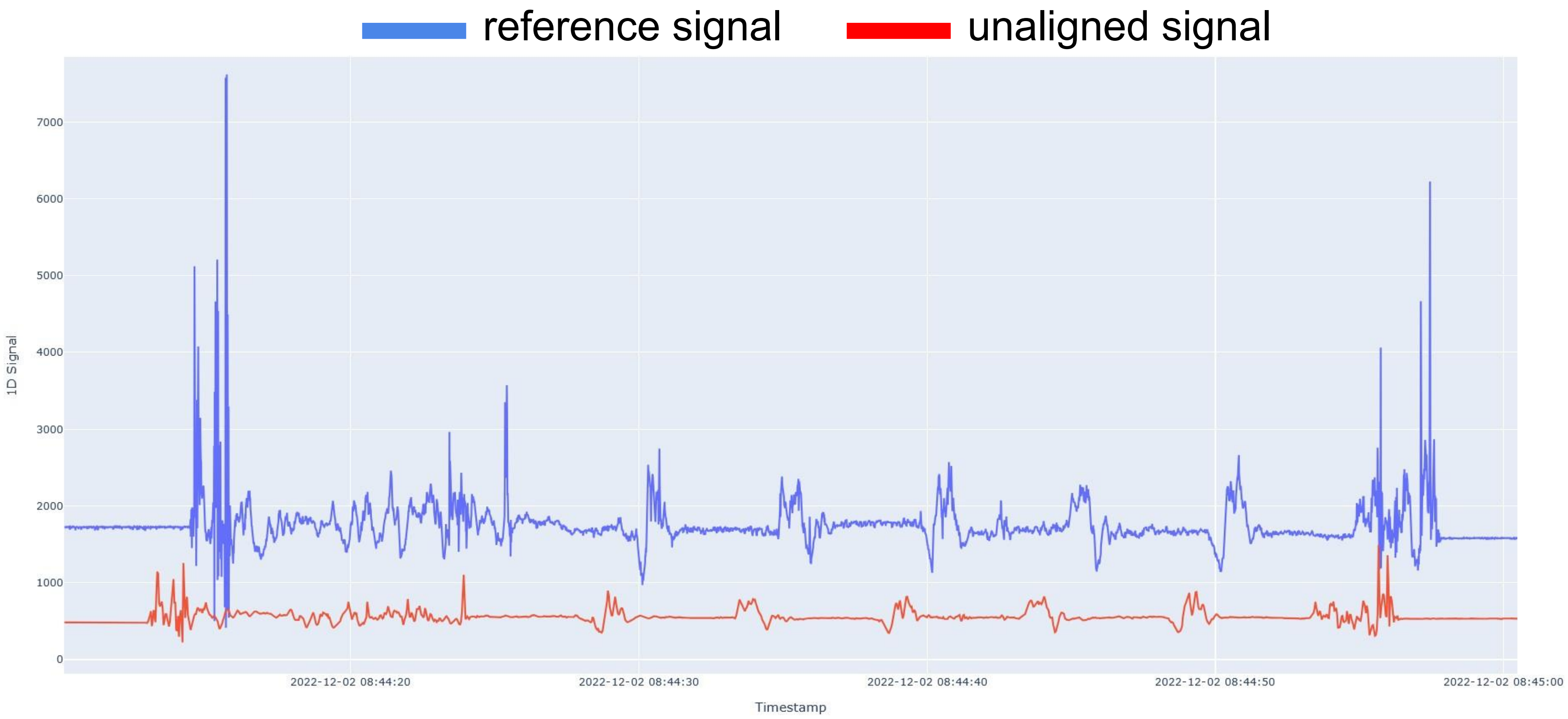


Goal

- Algorithm for data synchronization across multimodal sensors (viable for online)
- Aimed error: < 20% of time from window for Activities of Daily Living (ADL) classifier

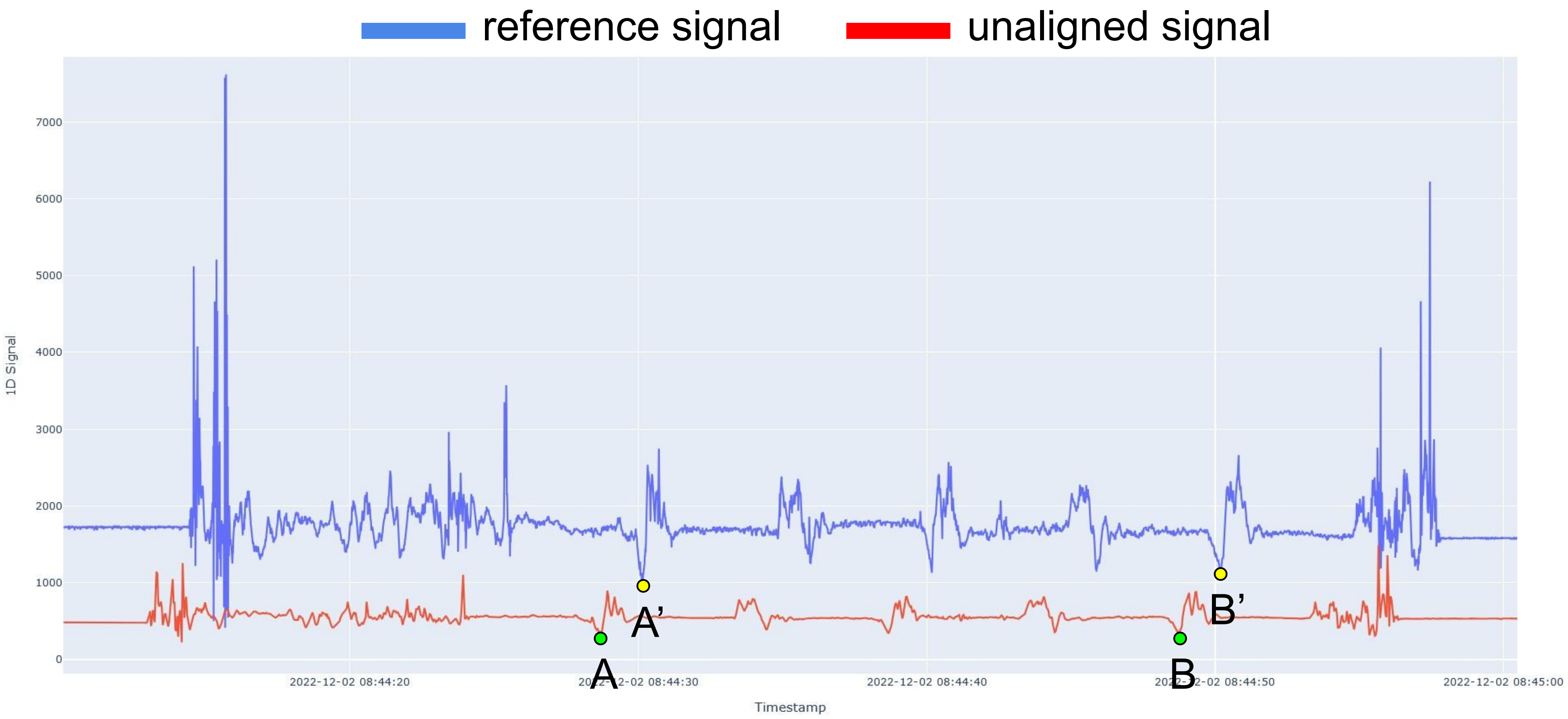


Creating a Ground Truth Dataset



Creating a Ground Truth Dataset

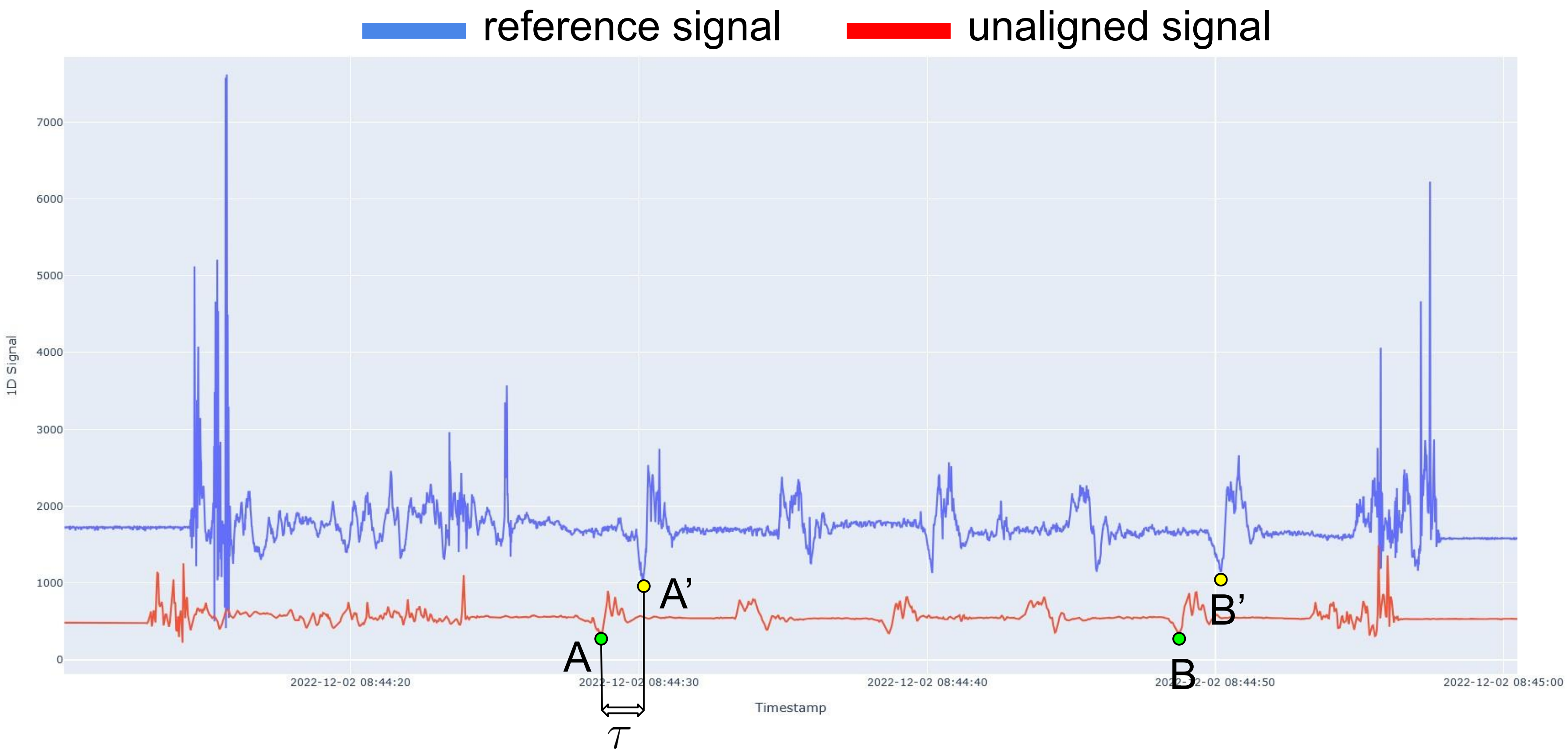
Identify 2 pairs of **corresponding points** (A, A’) and (B, B’)



Creating a Ground Truth Dataset

Shift the whole align by

$$\tau = A'_t - A_t$$



Creating a Ground Truth Dataset

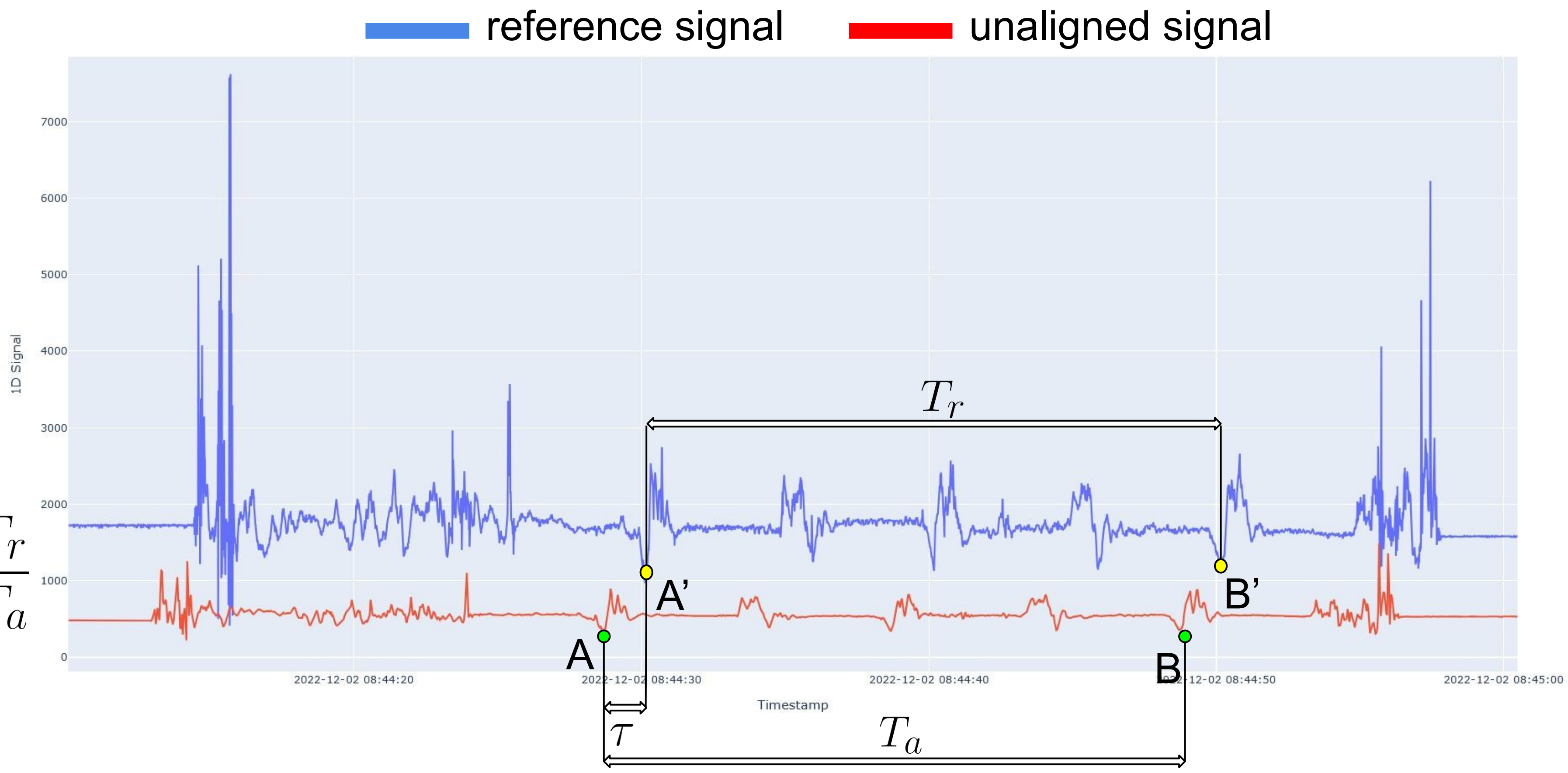
Shift the whole align by

$$\tau = A'_t - A_t$$

Stretch everything by $\frac{T_r}{T_a}$, with A used as the reference point

$$P^*_t = A_t + \tau + (P_t - A_t)\frac{T_r}{T_a}$$

P: any point on the unaligned signal



Creating a Ground Truth Dataset

Shift the whole align by

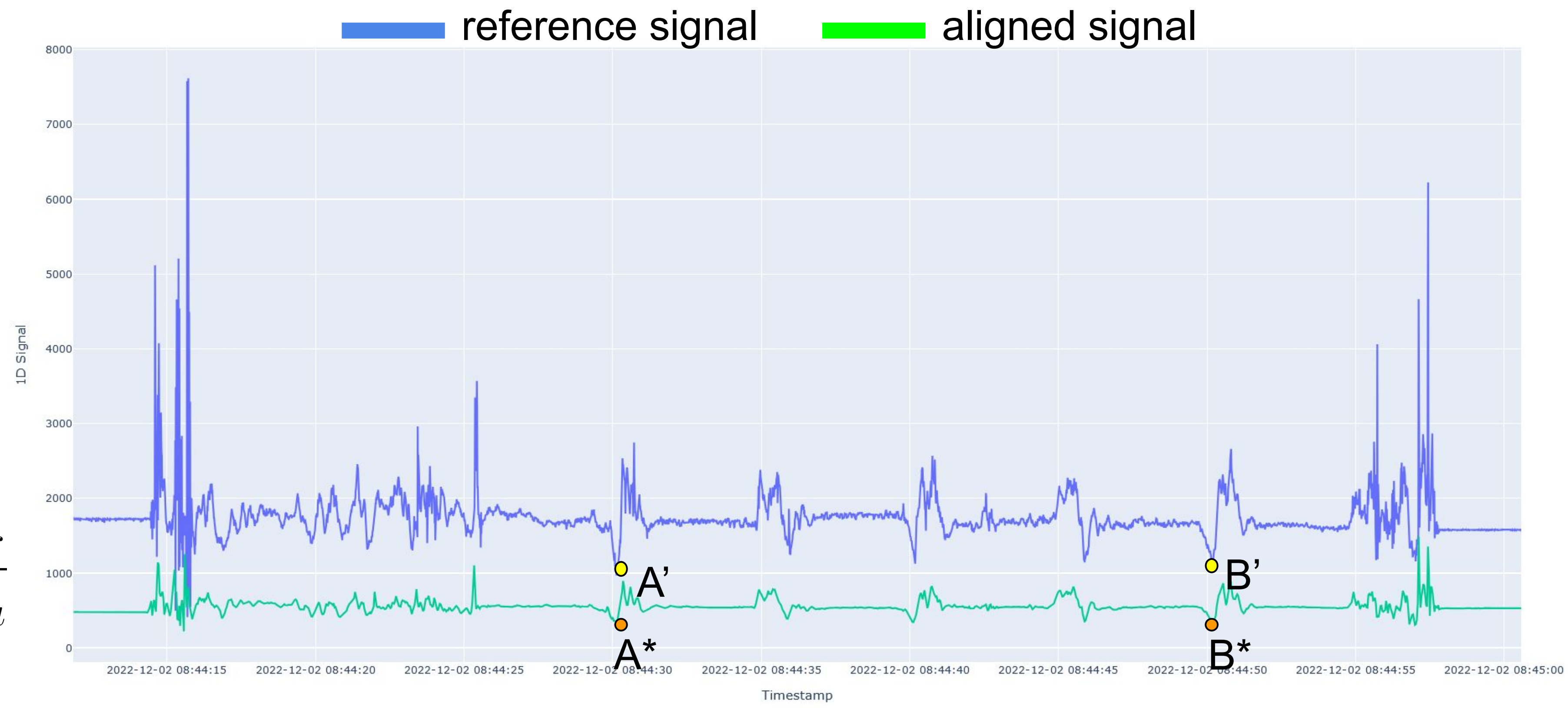
$$\tau = A'_t - A_t$$

Stretch everything by $\frac{T_r}{T_a}$, with A used as the reference point

$$P^*_t = A_t + \tau + (P_t - A_t)\frac{T_r}{T_a}$$

$$\rightarrow \begin{array}{l} A^*_t = A'_t \\ B^*_t = B'_t \end{array}$$

$\rightarrow$ total: 18 signals



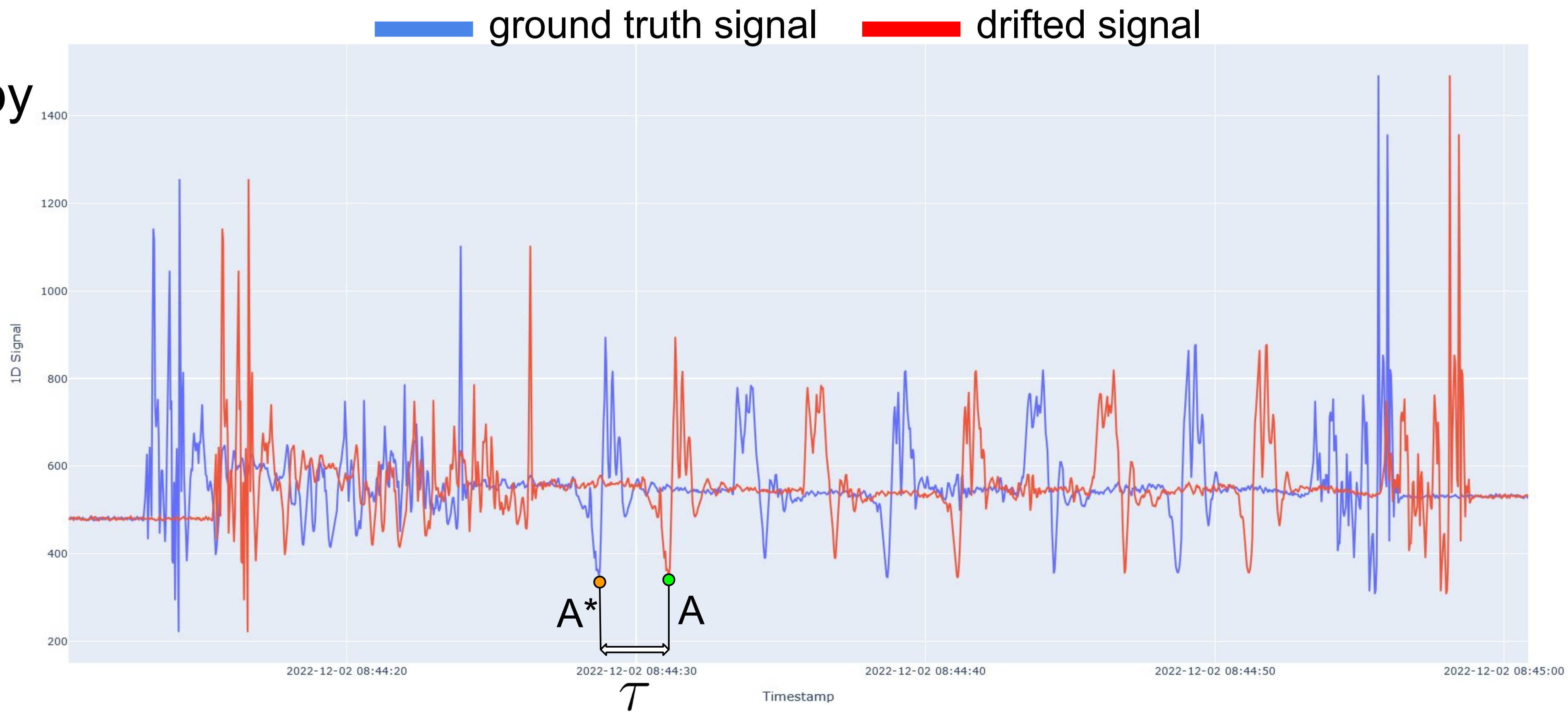
Creating a Drifted Dataset

Shift whole signal by [0.25, 0.5, 0.75, 1, 1.25, 1.5, 1.75, 2] seconds

$$\tau = A_t^* - A_t$$

$$P_t = P_t^* + \tau$$

P^*: any point on the ground truth signal



Methodology

- ‘Hardware’ based
  - sending current time to sensor via an api

    → Not possible due to sensors not providing this functionality

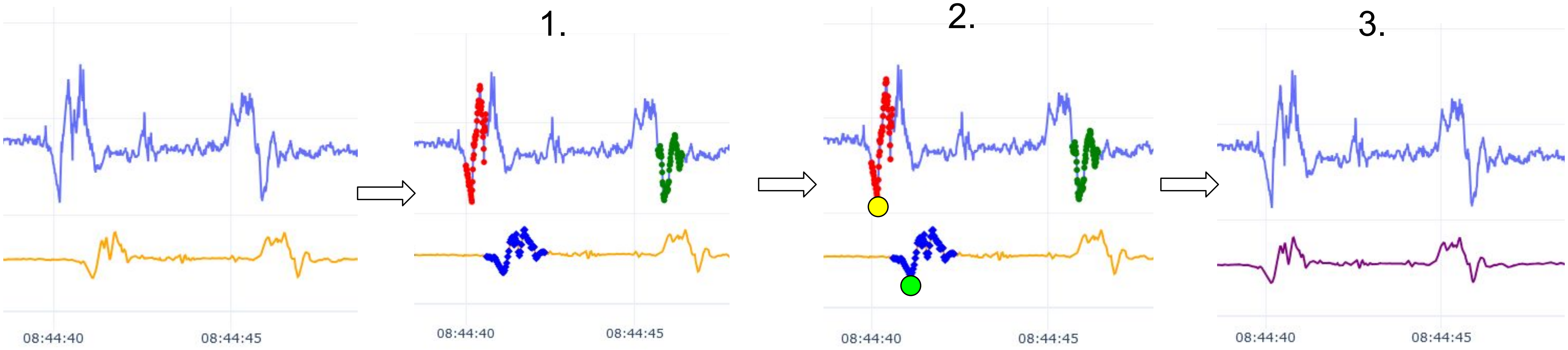
- Correlation based
  - works decently for signals sharing similarities

    Deep Canoncial Correlation Alignment, 2021
    Schütz, N., Botros, A., Single, M., Naef, A. C., Buluschek, P., & Nef, T.

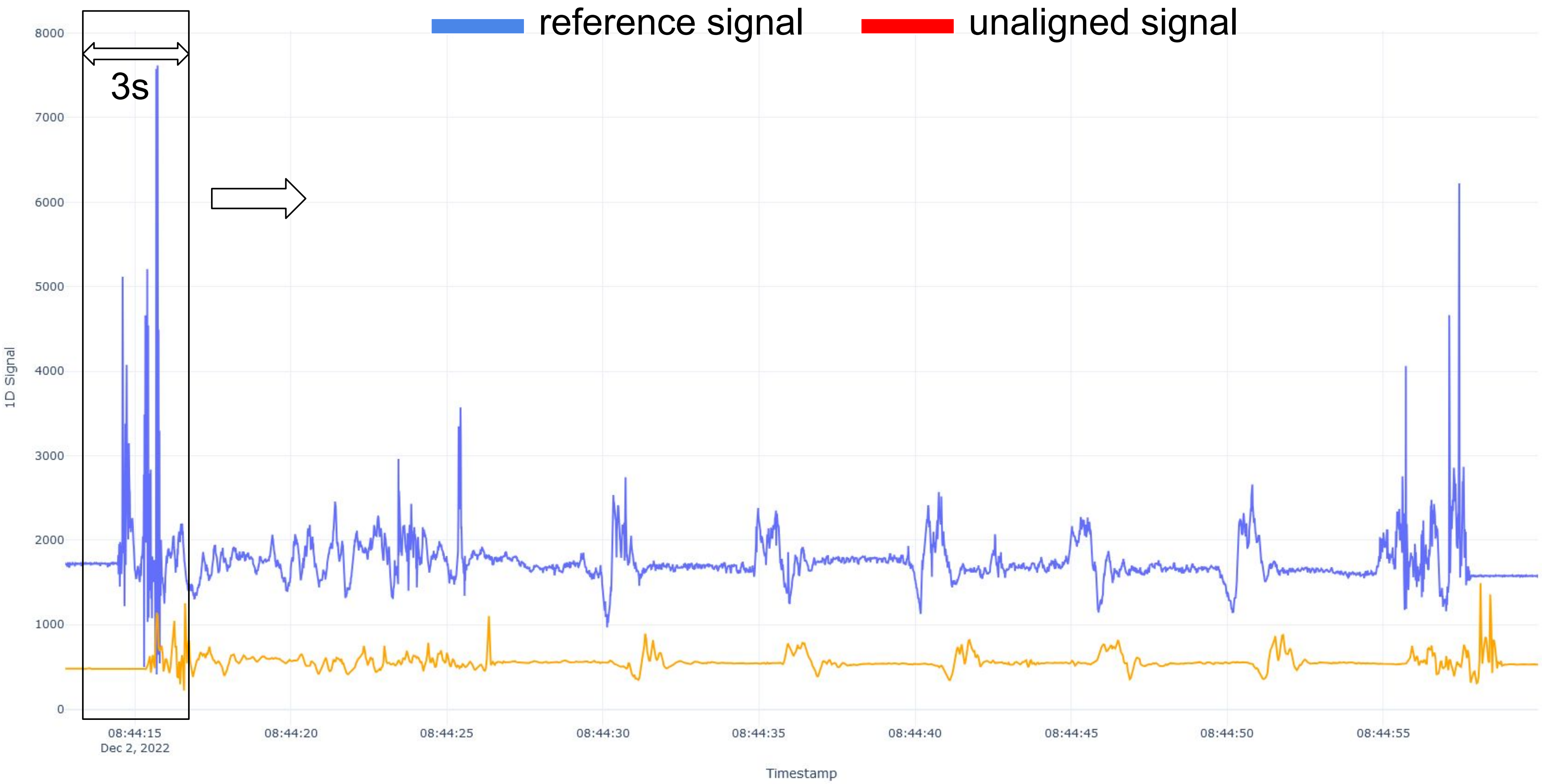
    - Segment signals into smaller segments
    - Signals passed through neural networks learning mapping to shared latent space
    - Canonical Correlation Analysis to maximize correlation
    - Construct warping function by combining local alignments

Methodology - Event Based

1. Detect events in each signal
2. Match corresponding events from both signals
3. Align the signals

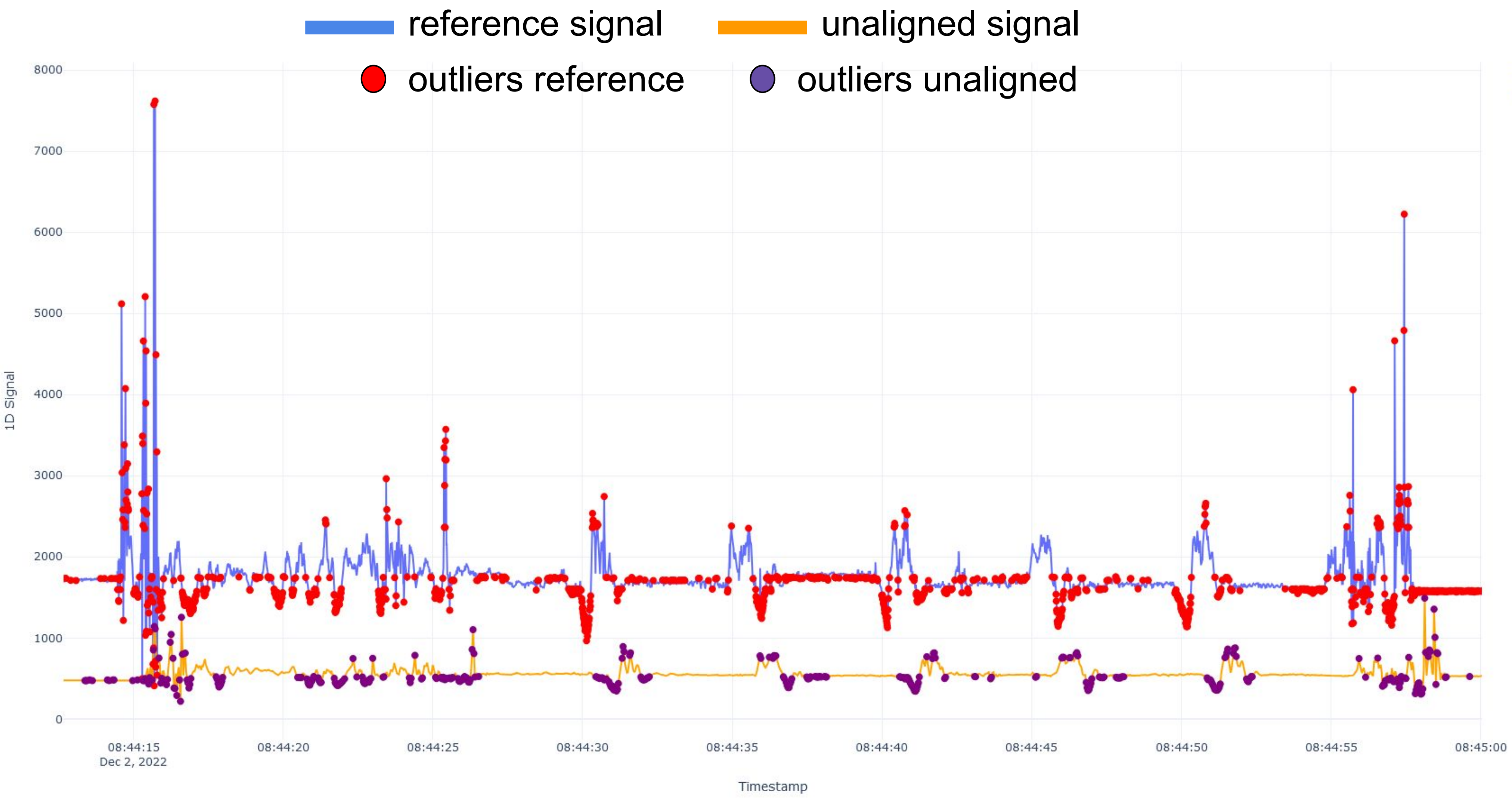


Example


reference signal
unaligned signal
3s
8000
7000
6000
5000
4000
3000
2000
1000
0
1D Signal
08:44:15
Dec 2, 2022
08:44:20
08:44:25
08:44:30
08:44:35
08:44:40
08:44:45
08:44:50
08:44:55
Timestamp

Detect Outliers

Find outliers (using Local Outlier Factor)



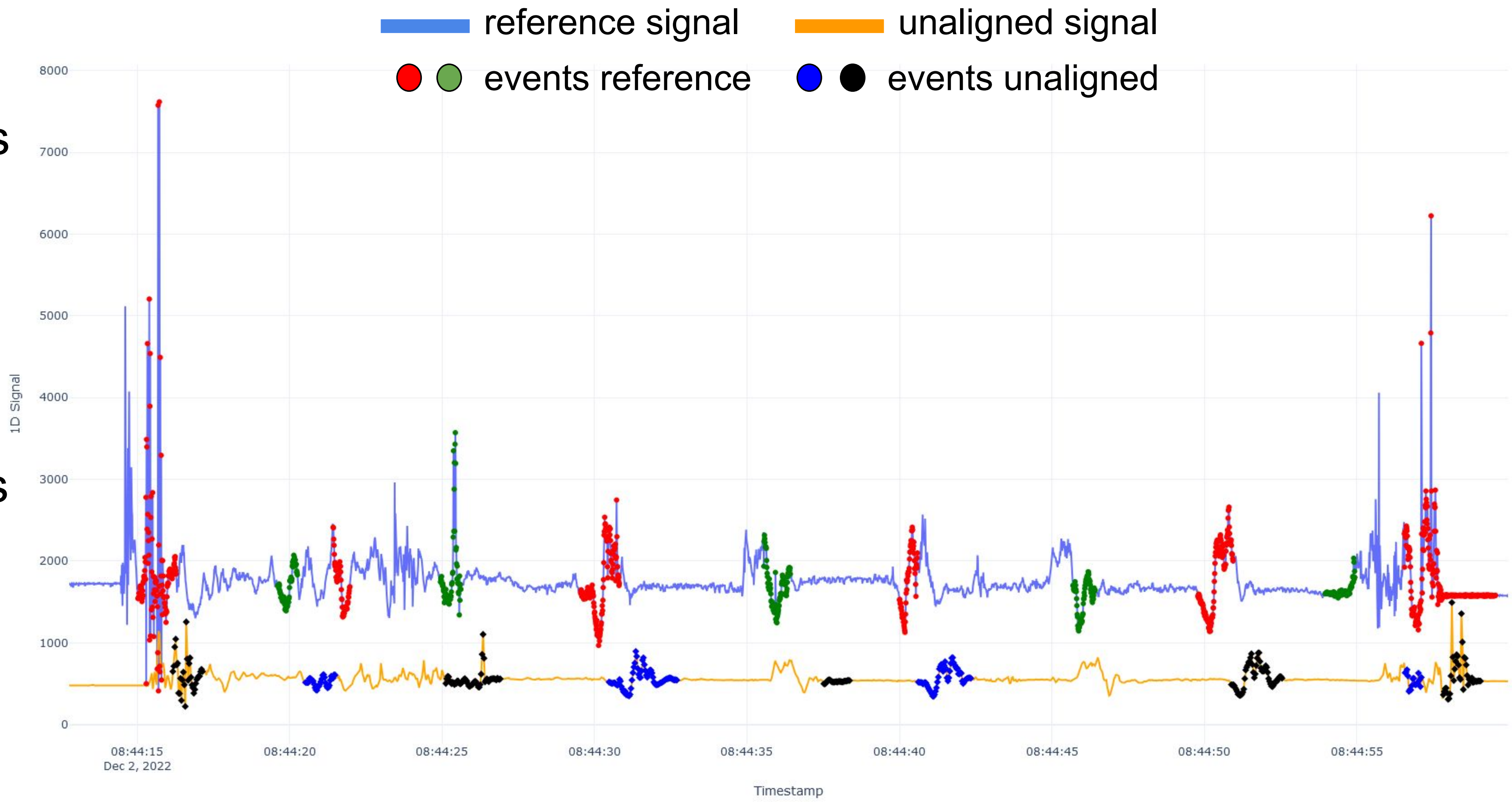
Cluster Events

Cluster outliers to events

event conditions:

duration > 0.5s

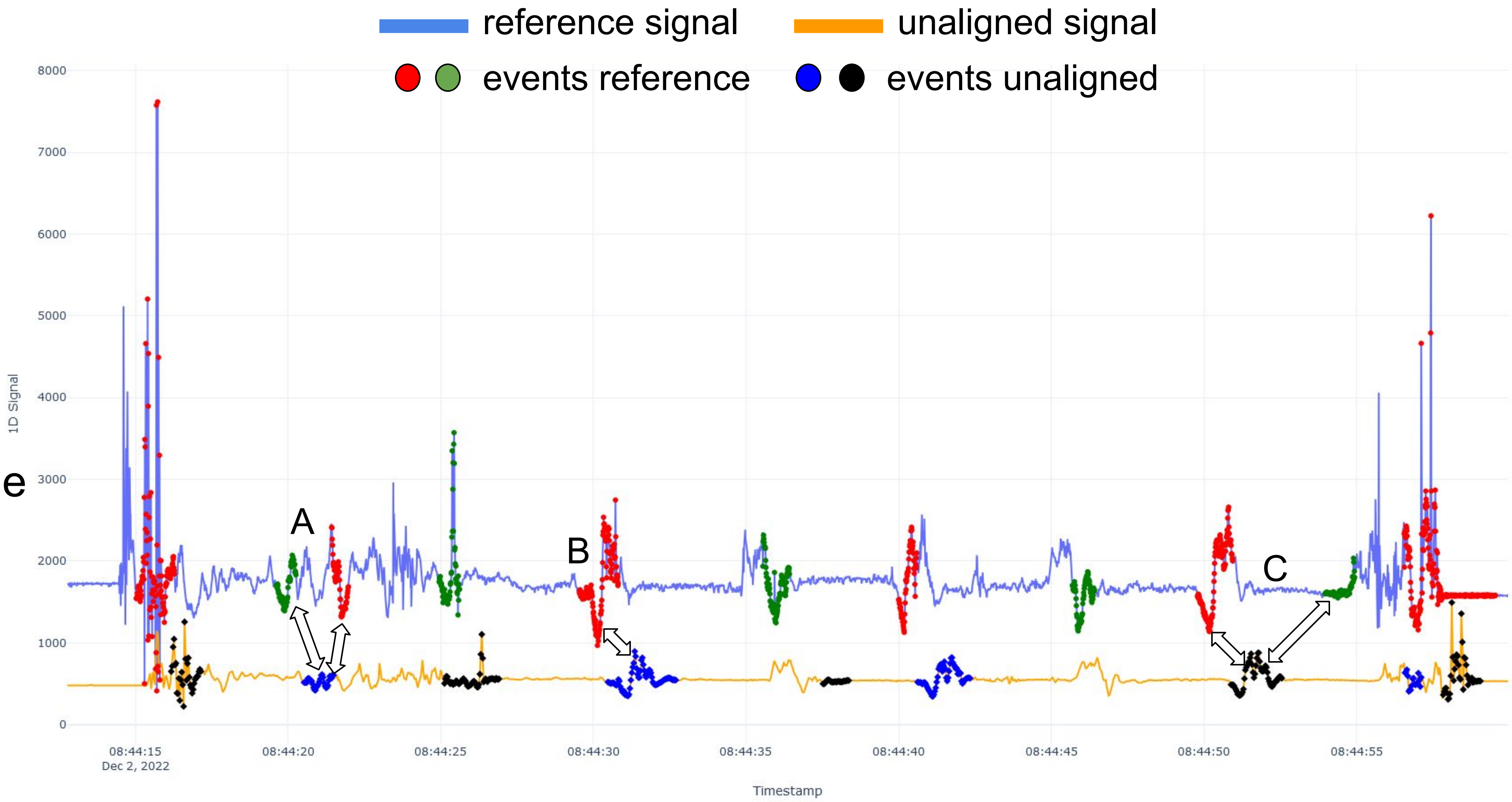
outlier fraction > 0.5



Match Events

Matching events

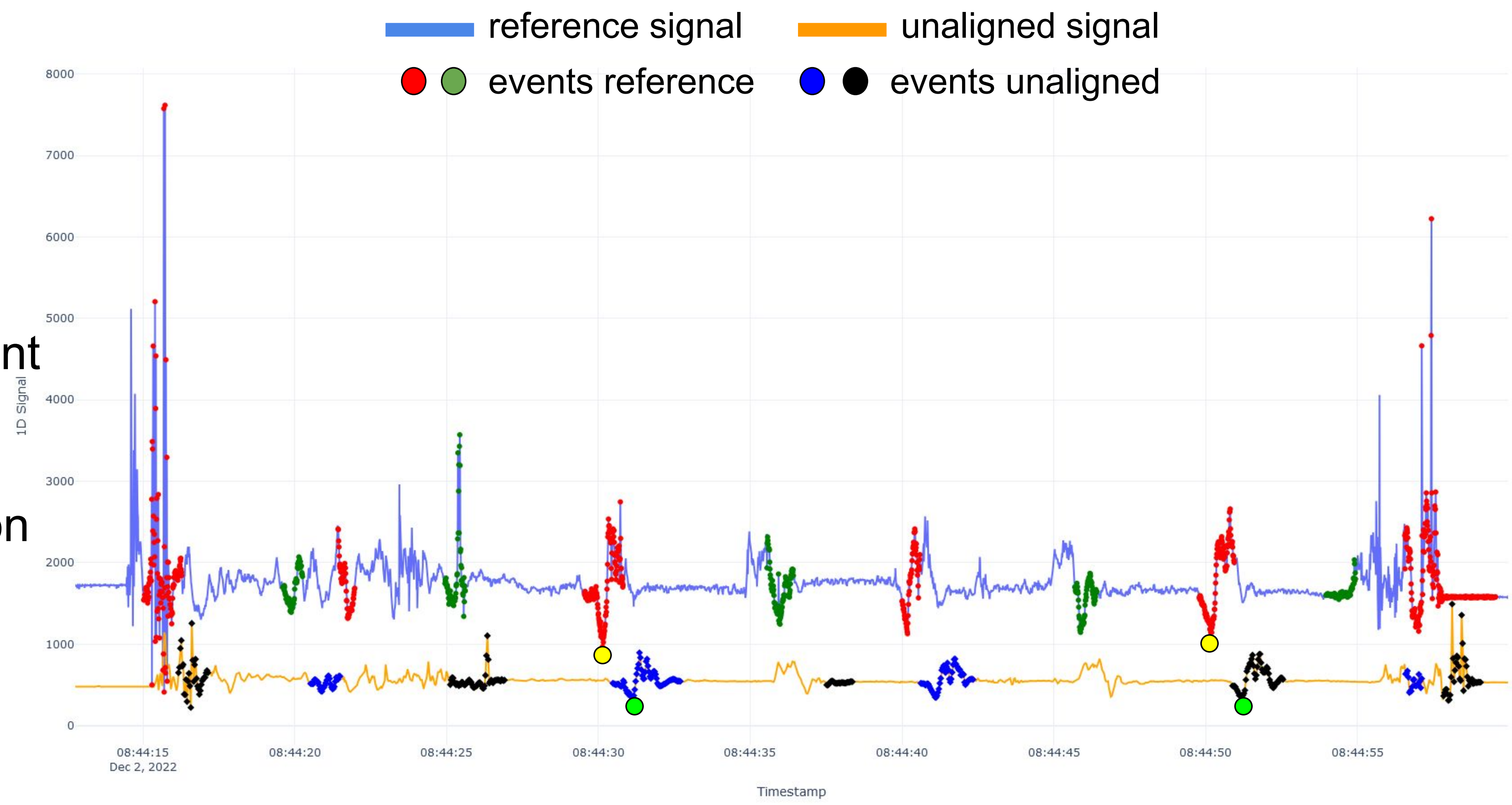
- Temporally close (2s)
- Normalize Event
- Dynamic time warping (DTW) distance < 150



Find synchronization Points

For matched events:

use lowest point from both events for synchronization



Align

Stretch signal linearly by adjusting the timestamps

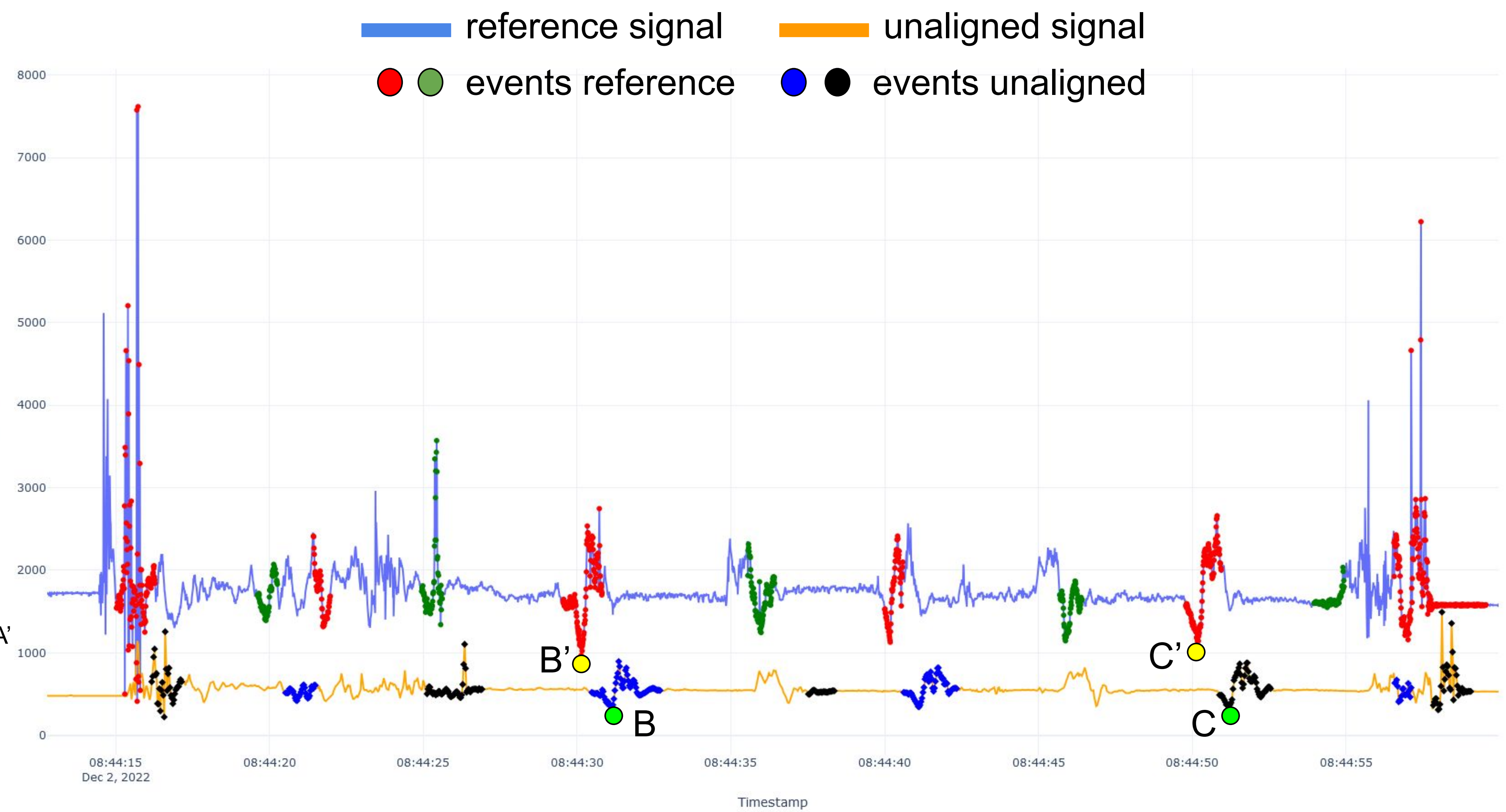
$$P^* = A + (P - A)\frac{T_r}{T_a}$$

A: last synchronization point

P: any point after A

T_r: passed reference time, B' - A'

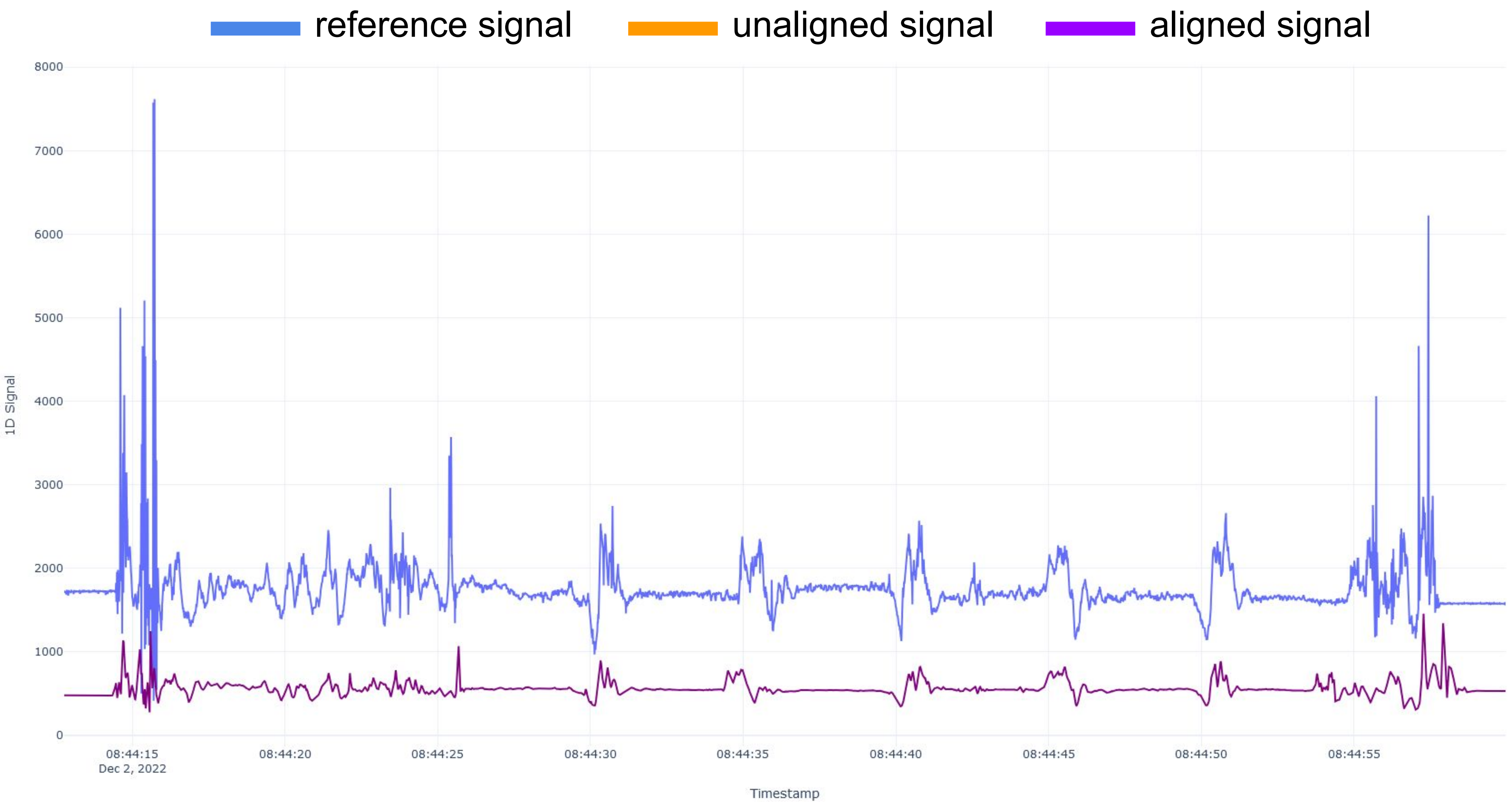
T_a: passed sensor time, B - A



Resample

Resample to reference frequency

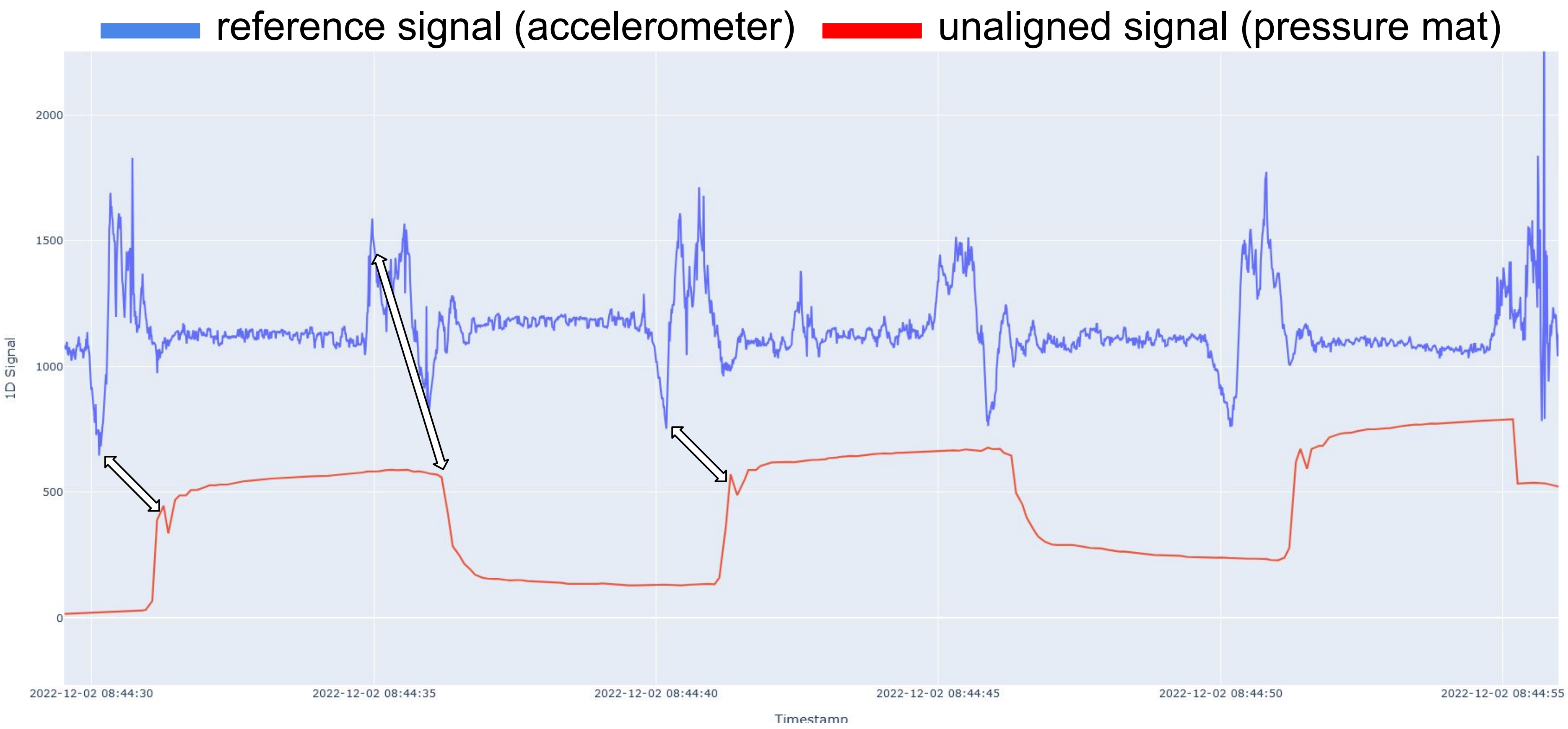
(1D linear interpolation)



Synchronization with Pressure Mat

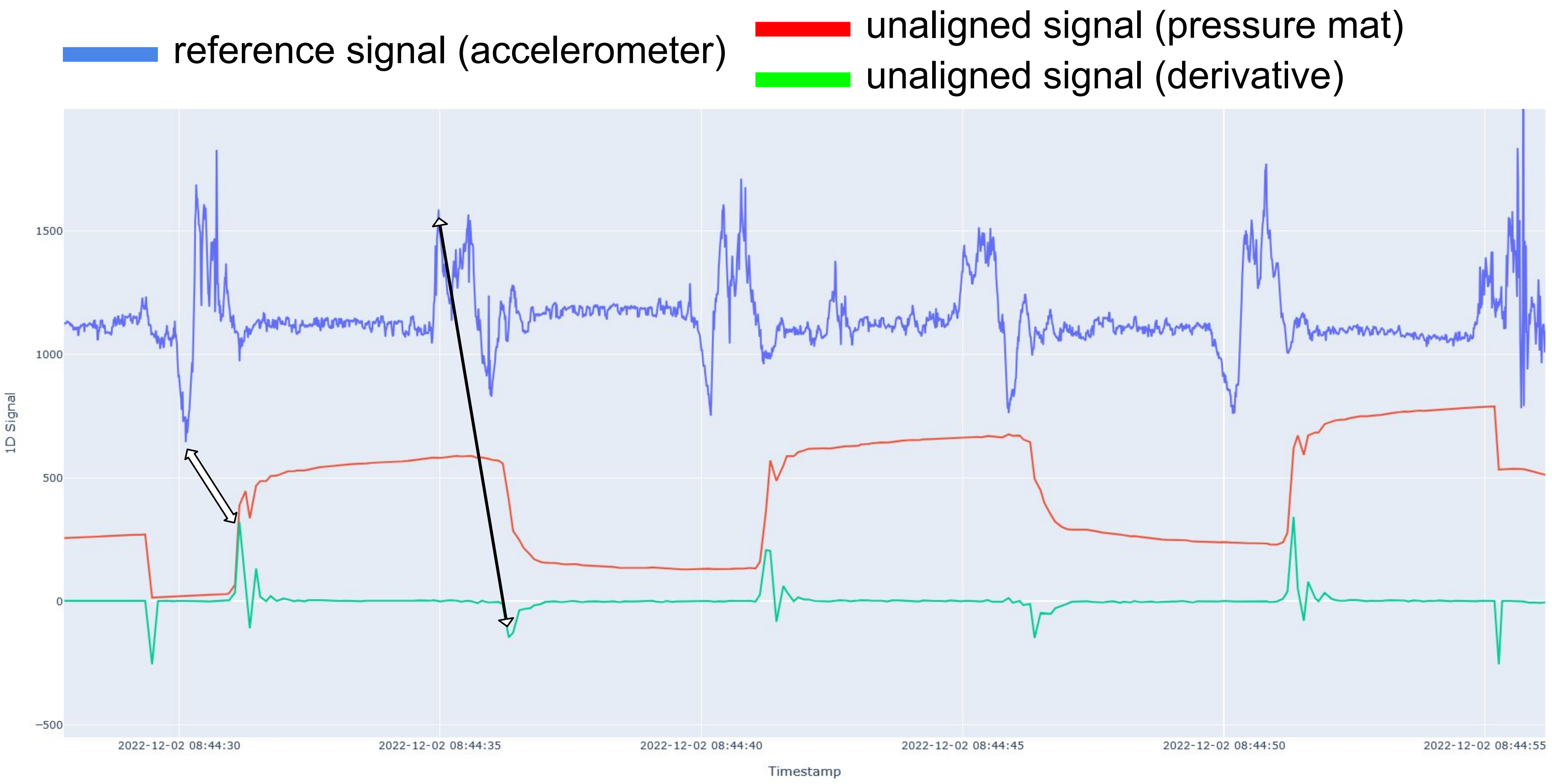
Pressure Mat:

- Signal is very different from accelerometer
- custom rules



Synchronization with Pressure Mat

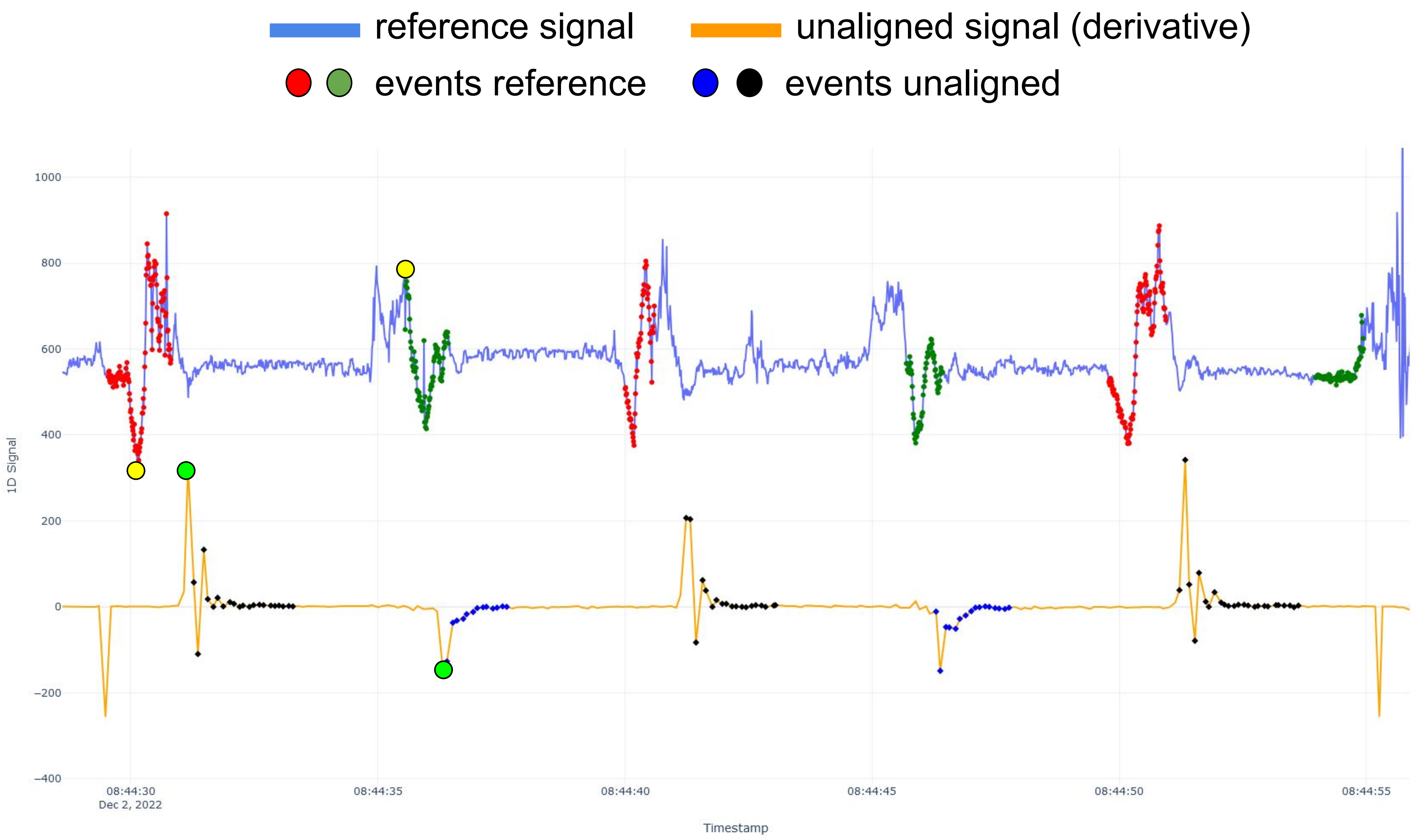
Work on derivative



Synchronization Points

For matched events:

minimum of reference and maximum pressure mat, resp. other way round



Synchronization with Pressure Mat

Error Quantification

N synchronized signals

Mean Absolute Error (MAE):

$$\frac{1}{2N}\sum_{1}^{N}(|A_i^* - A_i| + |B_i^* - B_i|)$$

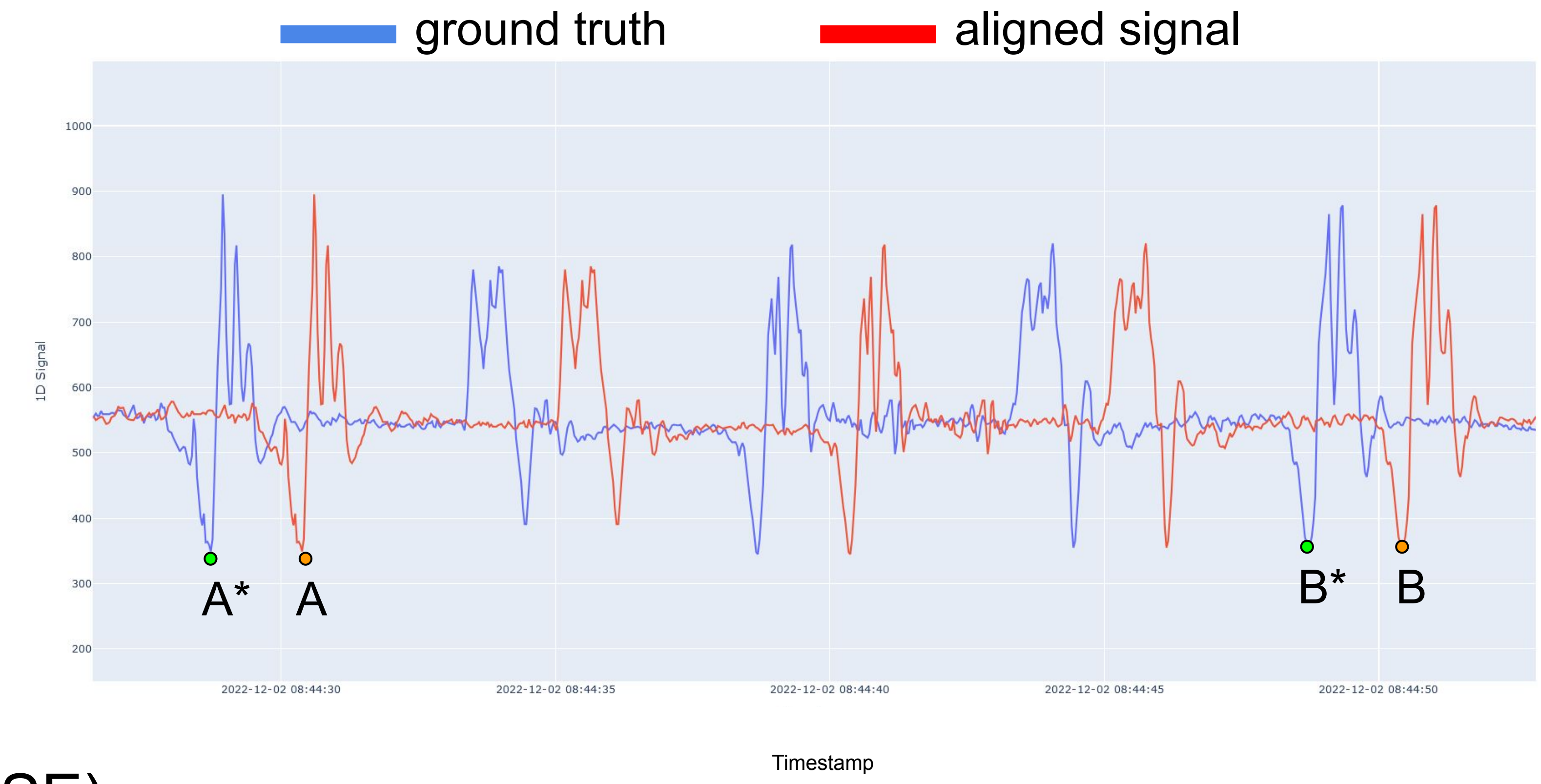
Standard deviation of error:

$$\sqrt{\frac{1}{2N}\sum_{1}^{N}((|A_i^* - A_i| - \mu)^2 + (|B_i^* - B_i| - \mu)^2)}$$

μ : mean of differences

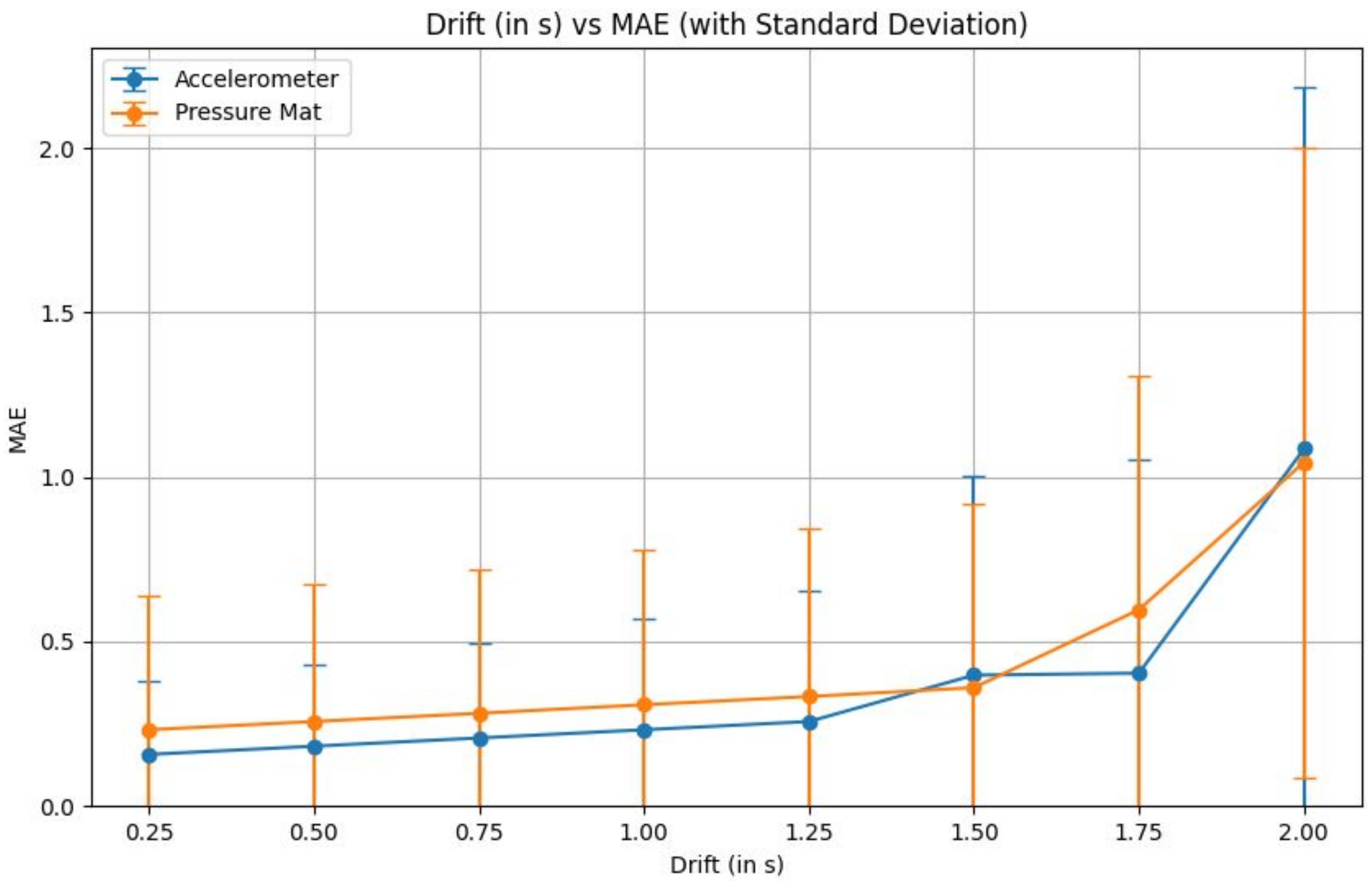
Root Mean Squared Error (RMSE):

$$\sqrt{\frac{1}{2N}\sum_{i=1}^{N}((A_i^* - A_i)^2 + (B_i^* - B_i)^2)}$$

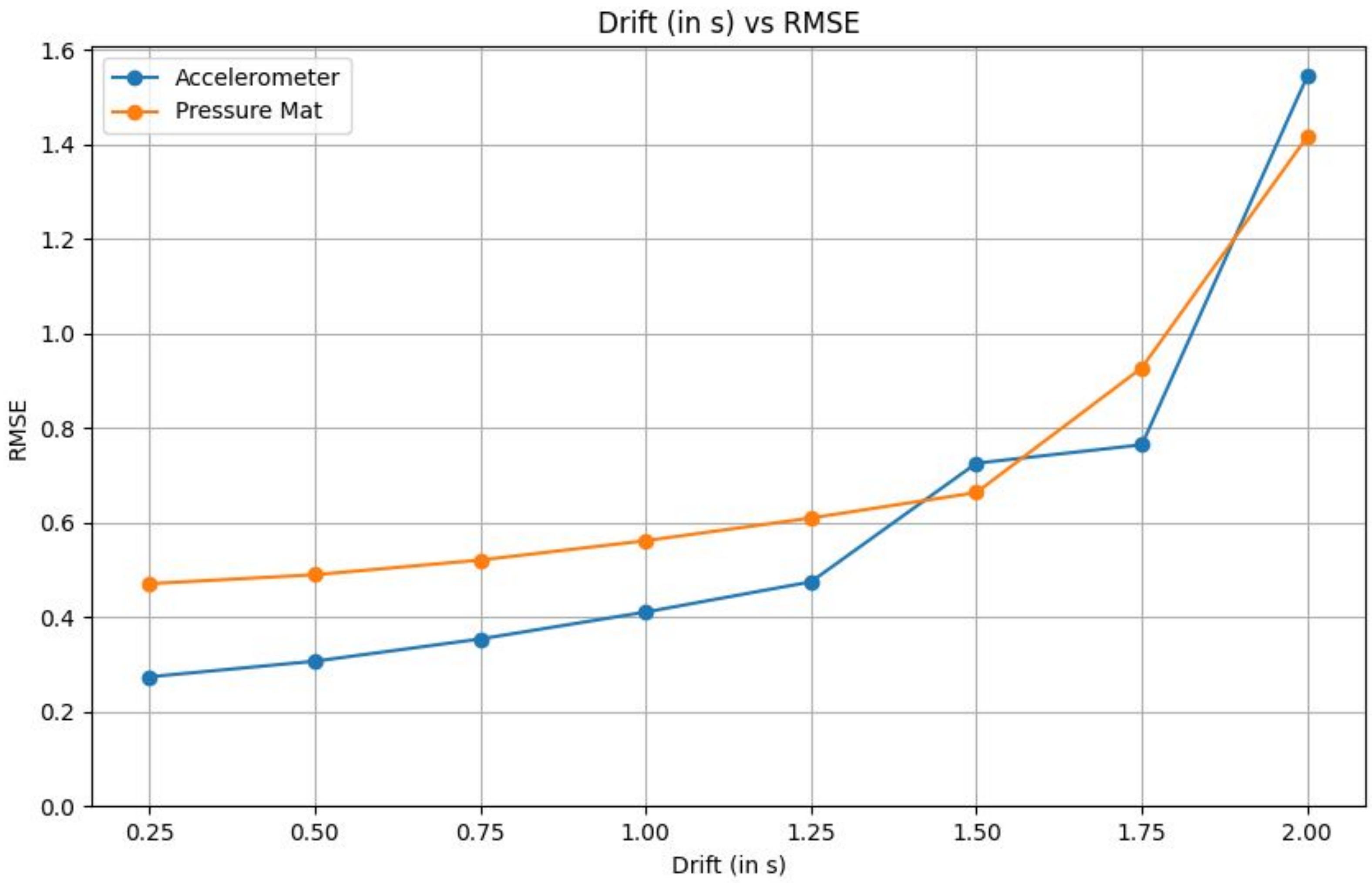


Accelerometer - Accelerometer: 10 signals
Accelerometer - Pressure Mat: 20 signals

Error Quantification Results

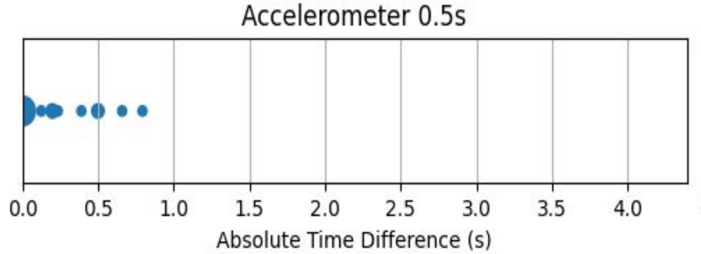


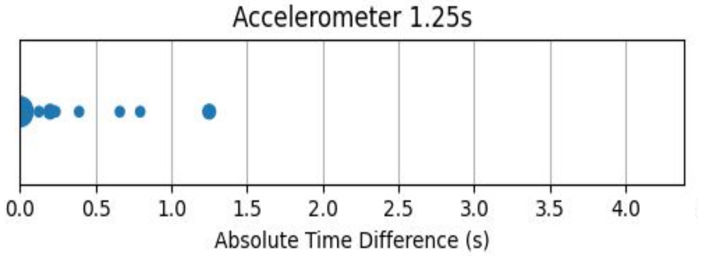
Error Quantification Results

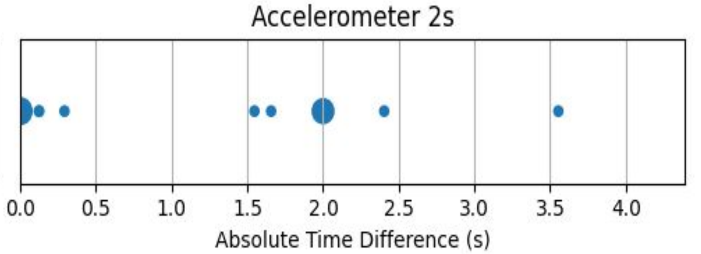


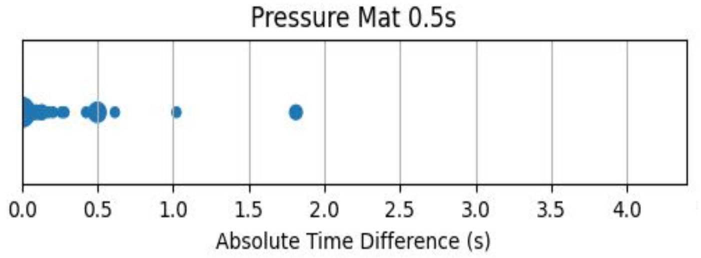
Error Quantification Results

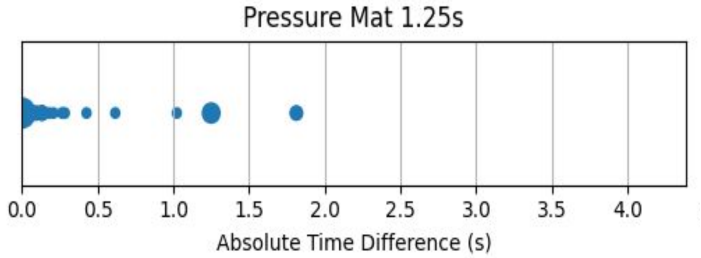
Plots for all absolute differences points per drifted set
- Accelerometer: 20 datapoints
- Pressure Mat: 40 datapoints

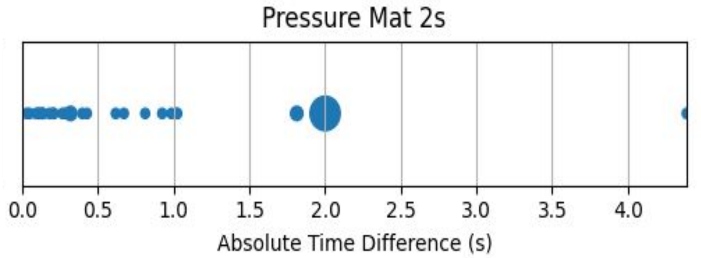












Conclusion

- Aimed error: < 20% of time from window for ADL classifier
  → currently not viable for 1s window
  → for 2s window viable, if manage to synchronize at least every ~12 hours.

Accelerator synched to Accelerator

Drift (in s)	MAE	Standard Deviation
0.25	0.156	0.224
0.5	0.181	0.246
0.75	0.206	0.287
1	0.231	0.339
1.25	0.256	0.399
1.5	0.397	0.607
1.75	0.403	0.649
2	1.085	1.098

Pressure Mat synched to Accelerator

Drift (in s)	MAE	Standard Deviation
0.25	0.231	0.409
0.5	0.256	0.417
0.75	0.281	0.437
1	0.307	0.469
1.25	0.332	0.51
1.5	0.359	0.558
1.75	0.596	0.711
2	1.044	0.957

Potential Future Work

- Improve results by fine tuning parameters
- Do synch after multiple events found
- Swap method(s) in selective pipeline steps
- Test on larger dataset