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Microsoft

Sensor Fusion for Learning-based Motion Estimation in VR

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[1]University at Buffalo, SUNY

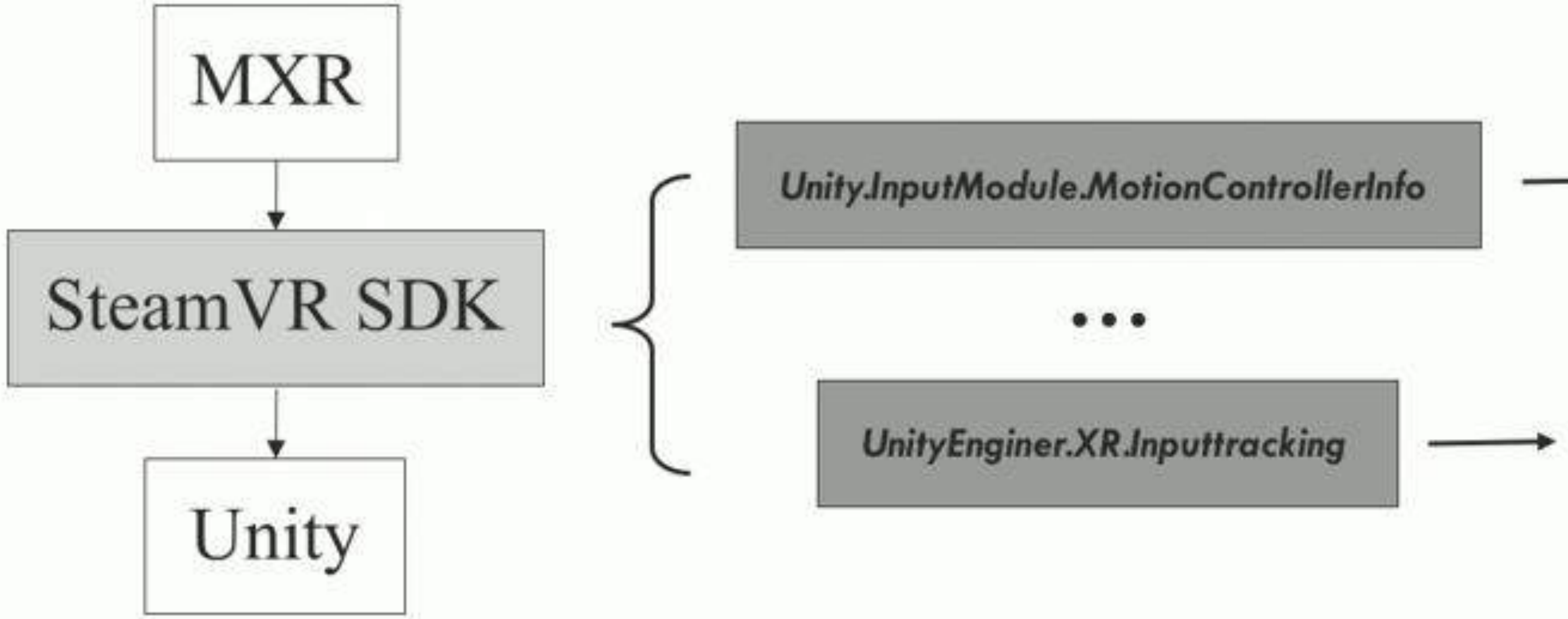
[2]Audio and Acoustics Research Group, Microsoft Research

Motion Tracking in VR

- For controller and head-mounted display (HMD)
- 3D orientation and position
- Continuously tracked over time
- Traditionally with computer vision
- Isotropic accuracy is important

How to Get Position Tracking Data

- For Windows Mixed Reality (MXR)

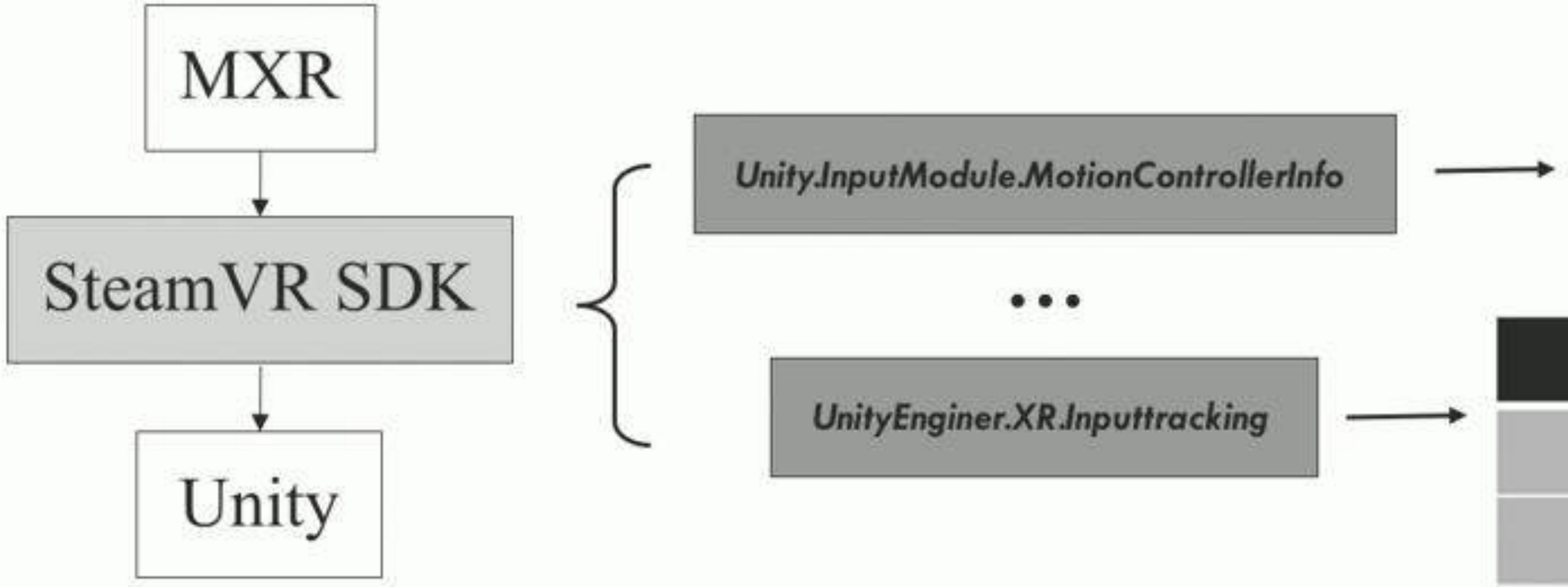


HMD		Controller	
Pos(xyz)	*Rot(xyz)*	*Pos(xyz)*	*Rot(xyz)*

Tracking State	Index	Accuracy (cm)
High	*2*	*< 7*
Approximate	*1*	*20~inf*
None	*0*	*---*

How to Get Position Tracking Data

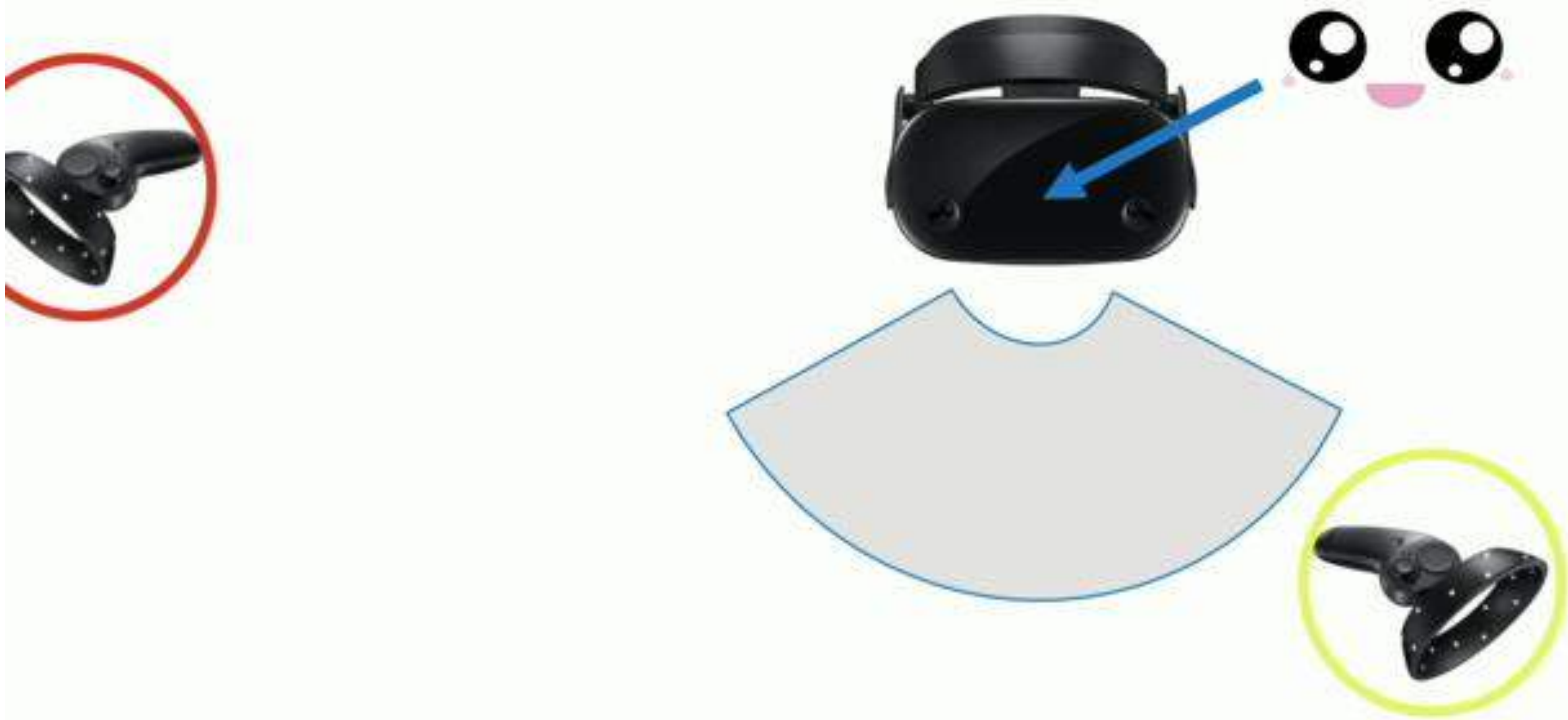
- For Windows Mixed Reality (MXR)

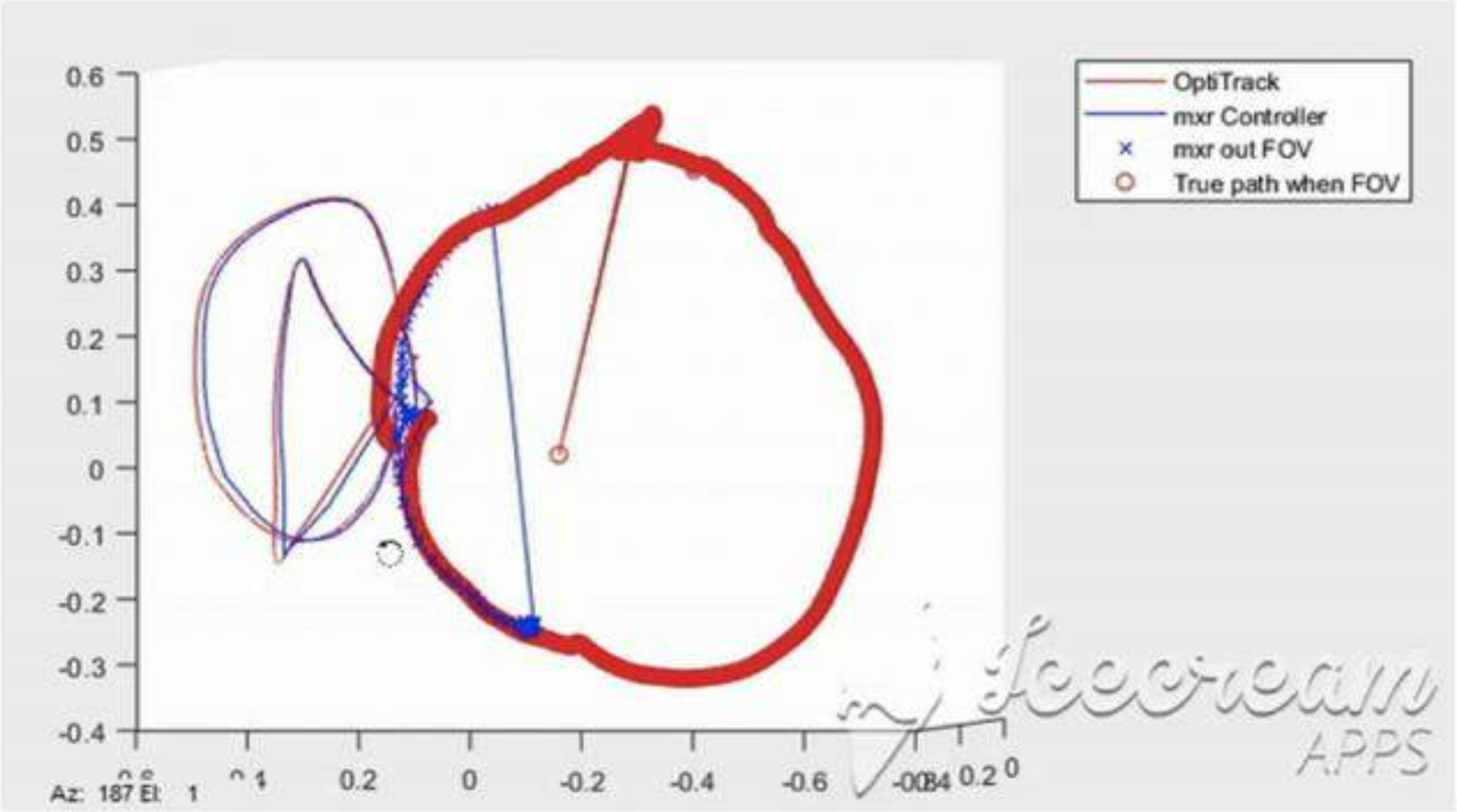


HMD		Controller	
Pos(xyz)	*Rot(xyz)*	*Pos(xyz)*	*Rot(xyz)*

Tracking State	Index
High	*2*
Approximate	*1*
Out of FOV	*4 consecutive 1*

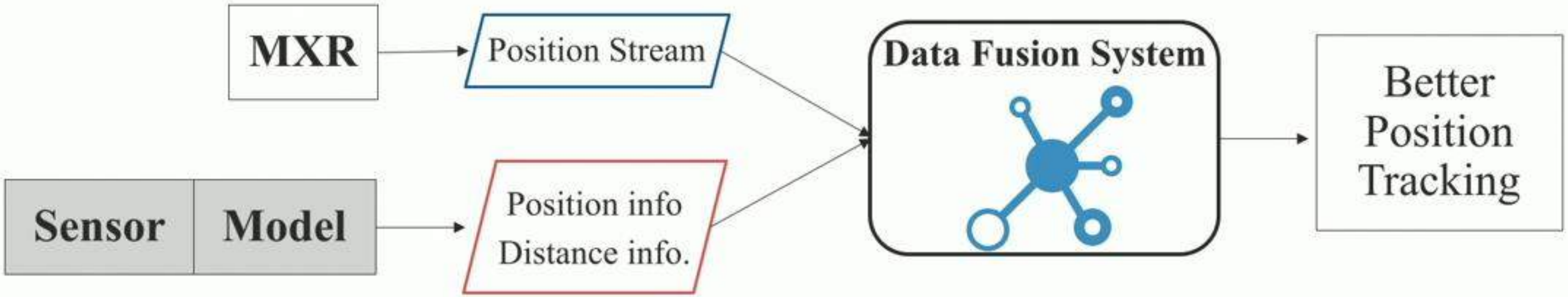
Performance of MXR Tracking





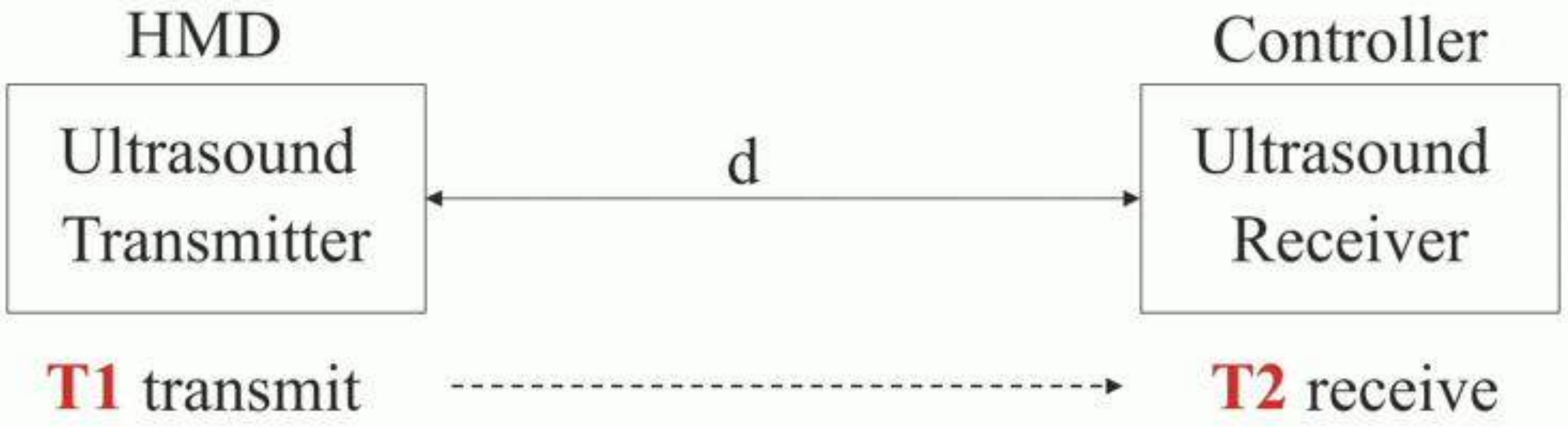
Proposed Approach

- Lightweight Sensor
- Learning-based Model
- Data Fusion System



1. Lightweight Sensor for Ultrasound Ranging

- Principle
  - Calculate the distance via time of flight

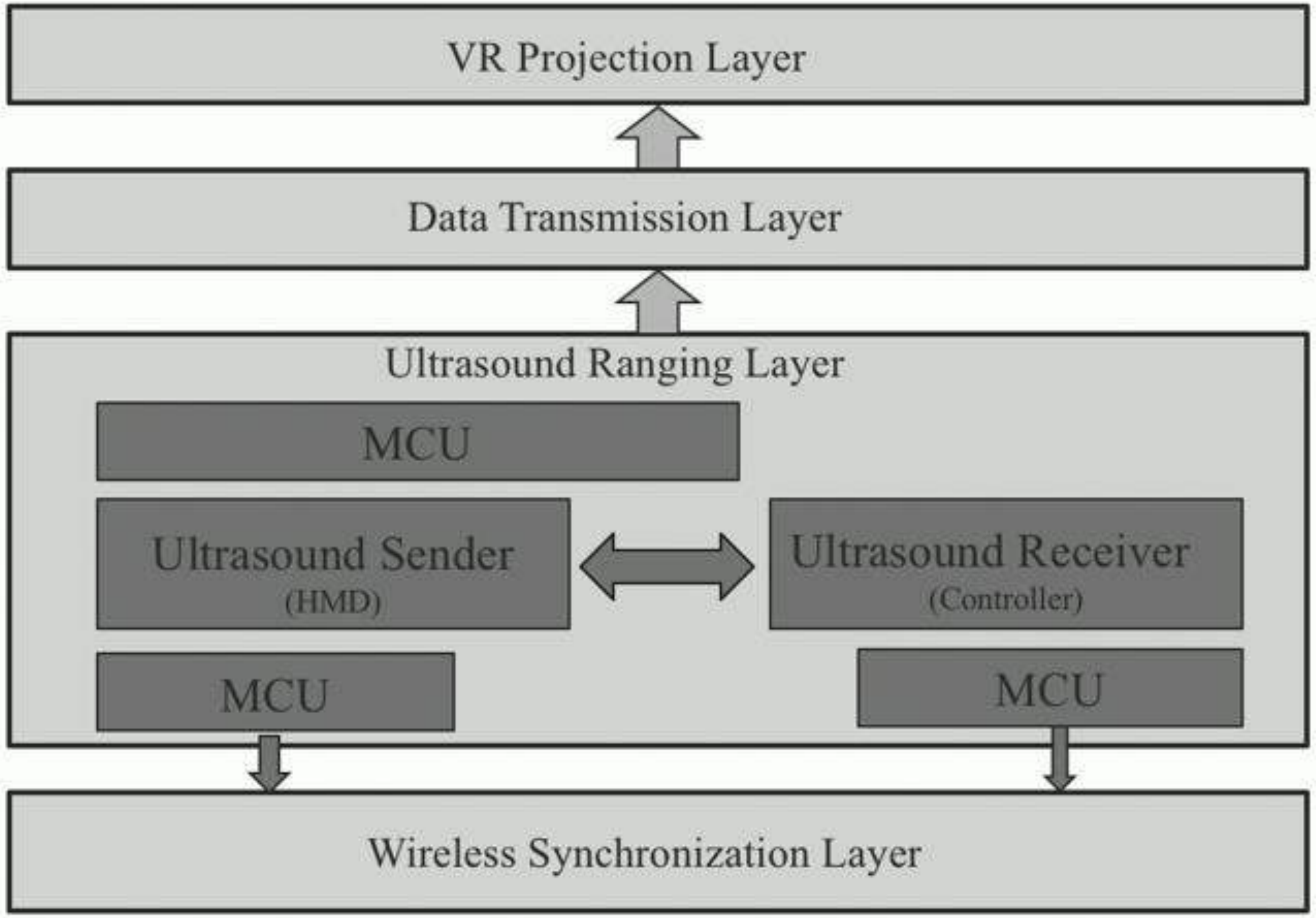


- $d = v_{sound} * (T2 - T1);$
- $v_{sound} = 331 + 0.6 * Temperature(m/s).$

Need time synchronization for accurate measurement

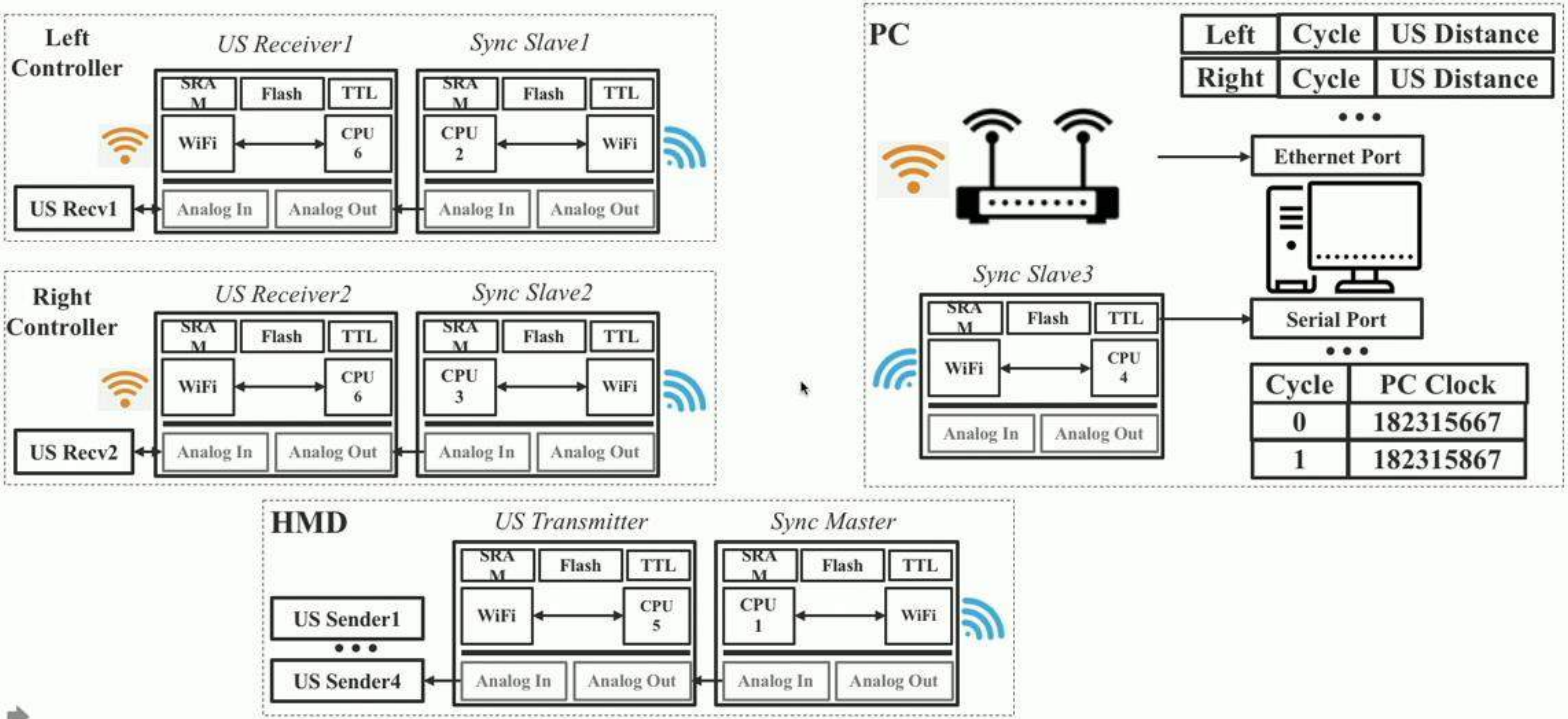
1. Lightweight Sensor for Ultrasound Ranging

- Architecture



1. Lightweight Sensor for Ultrasound Ranging

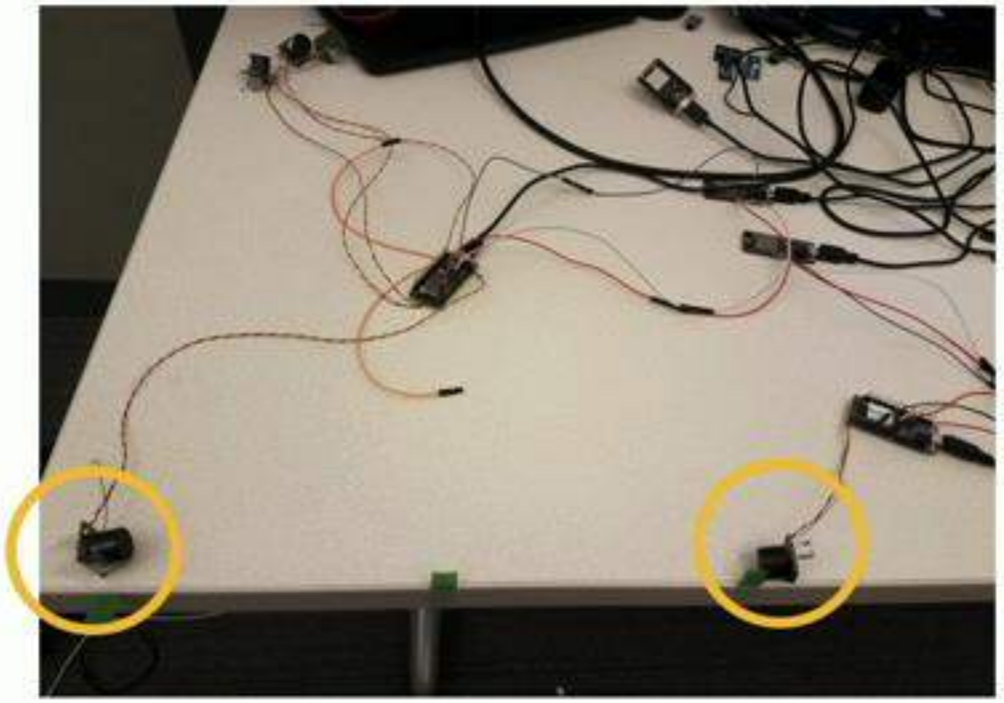
- Diagram

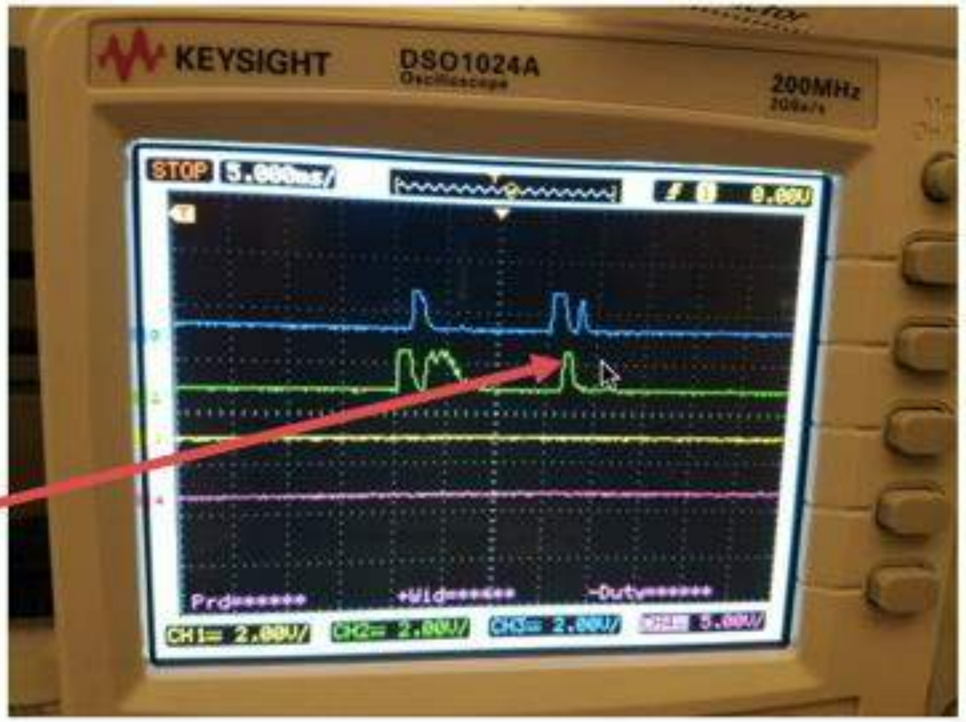


1. Lightweight Sensor for Ultrasound Ranging

- Hardware

MCU (Adafruit ESP8266)		Ultrasound Sensor (MB1330 MaxSonar)	
Frequency	*80 MHz*	***range***	*20-765 cm*
Flash	*4 MB*	***Rate***	*10 Hz*
Vdd	*3.3 V*	***Vdd***	*3.3-5.5 V*
Protocol	*WiFi UDP*	***Resolution***	*1 cm*
Total Power	*478 mW*	***Ultrasound Frequency***	*42 KHz*
Debugging Tool			
KeySight DSO1024A Oscilloscope (200 MHz)			





Time difference should match the physical distance.

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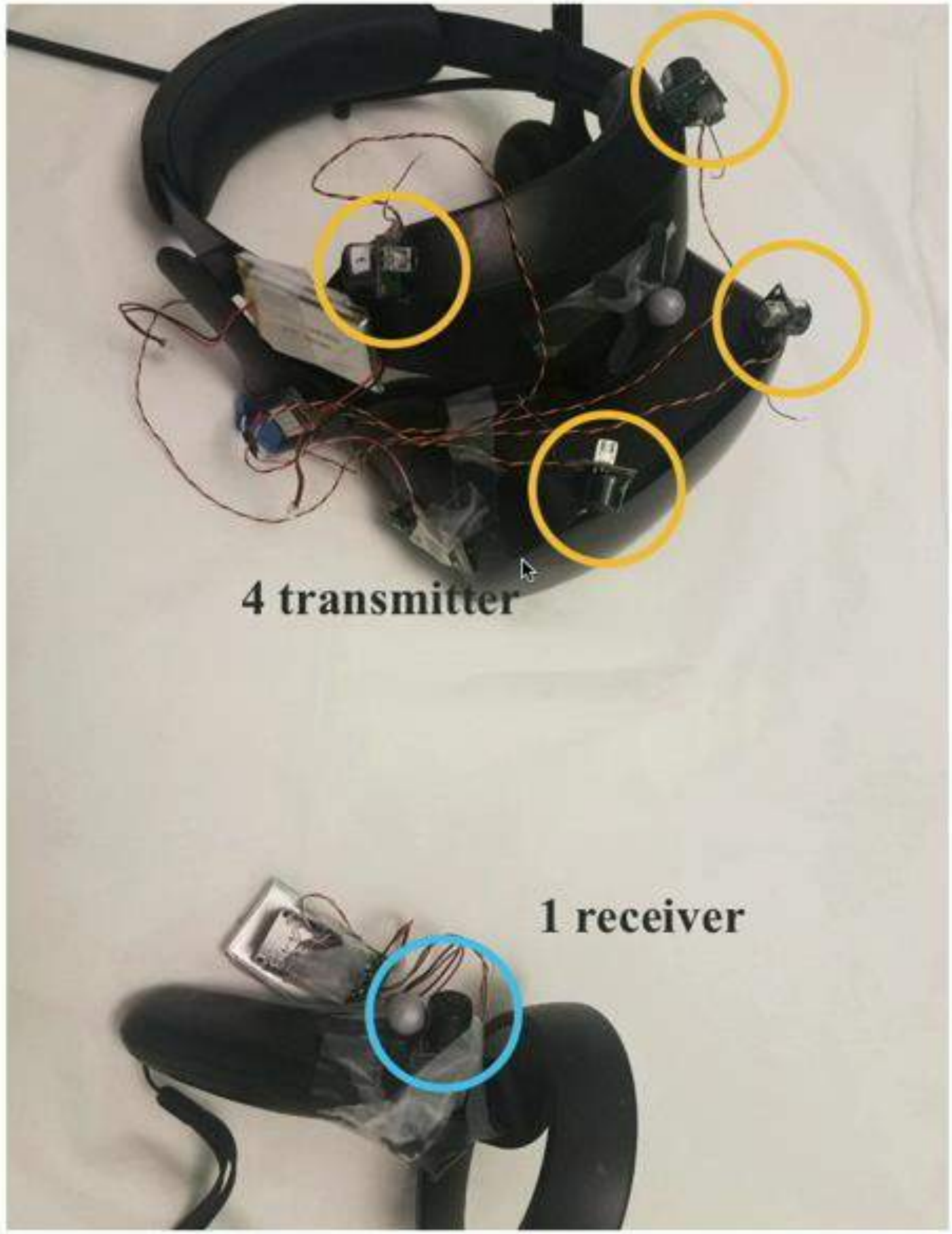

1. Lightweight Sensor for Ultrasound Ranging

- Synchronization performance
  - Bluetooth, Router WiFi have large random delay (upto 15 ms).
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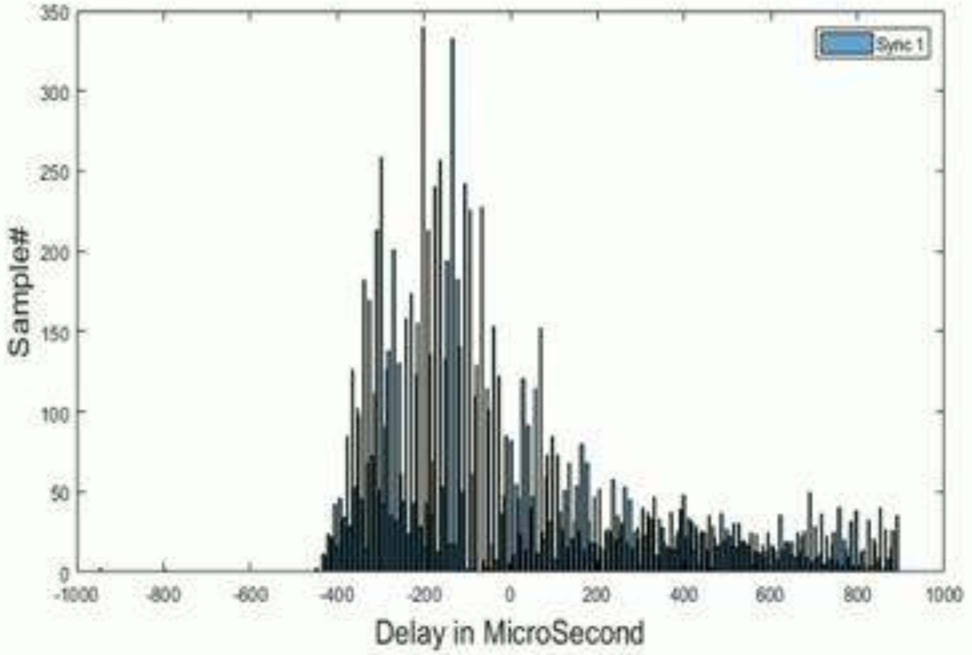

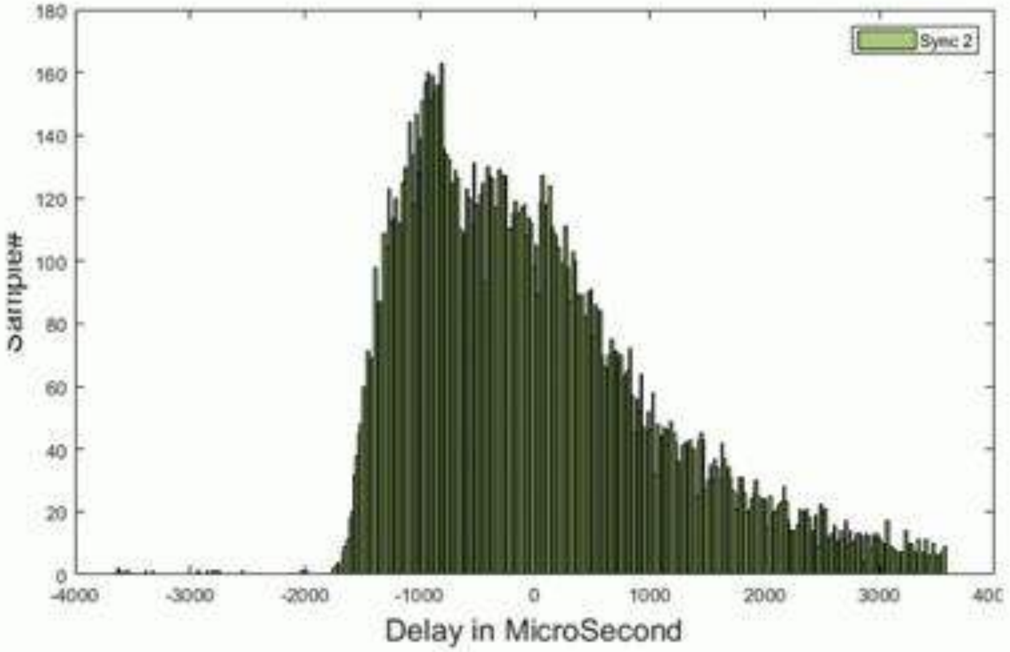

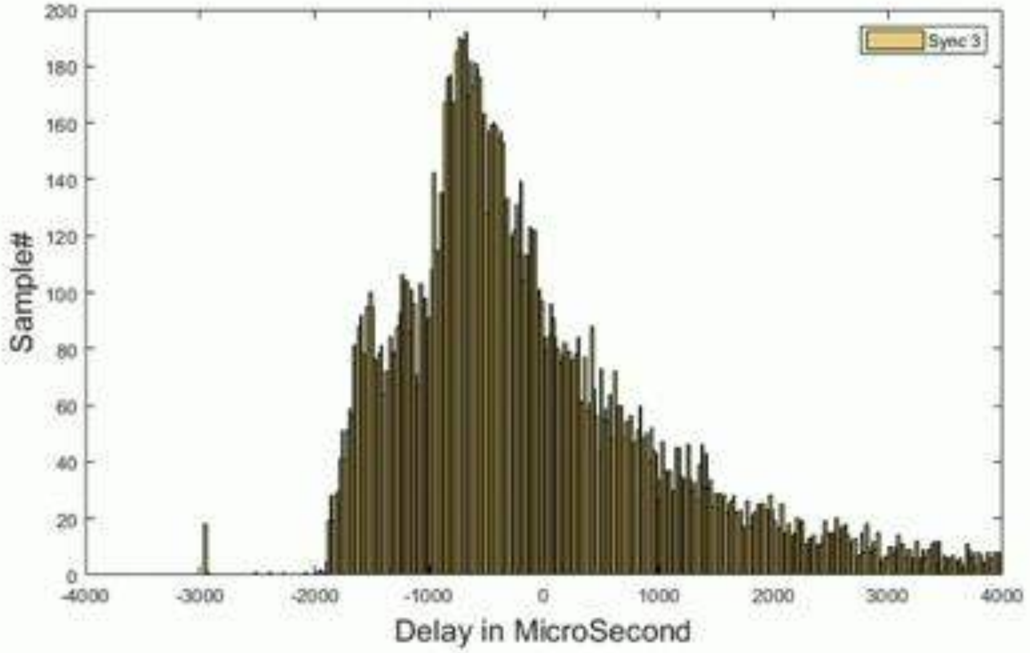

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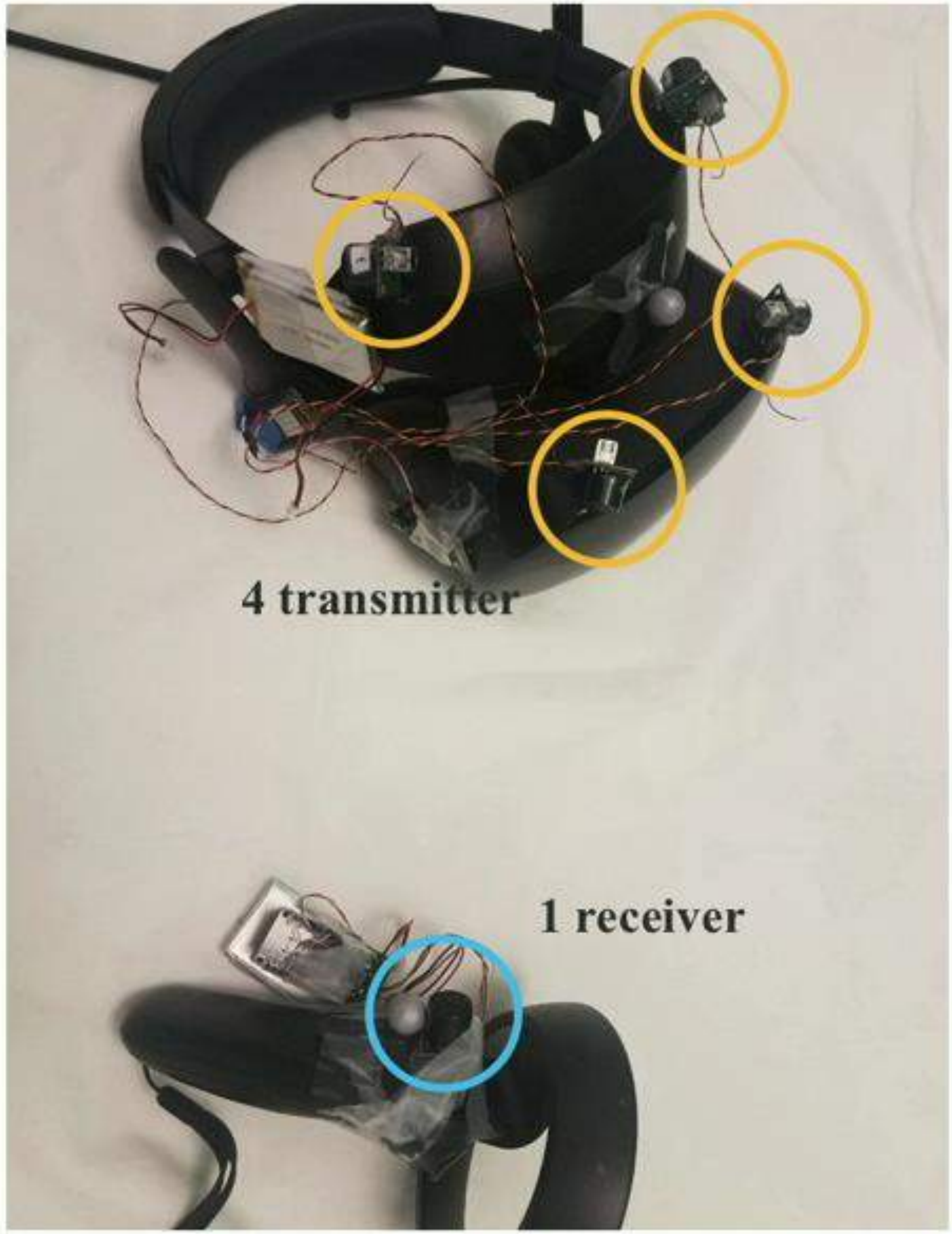

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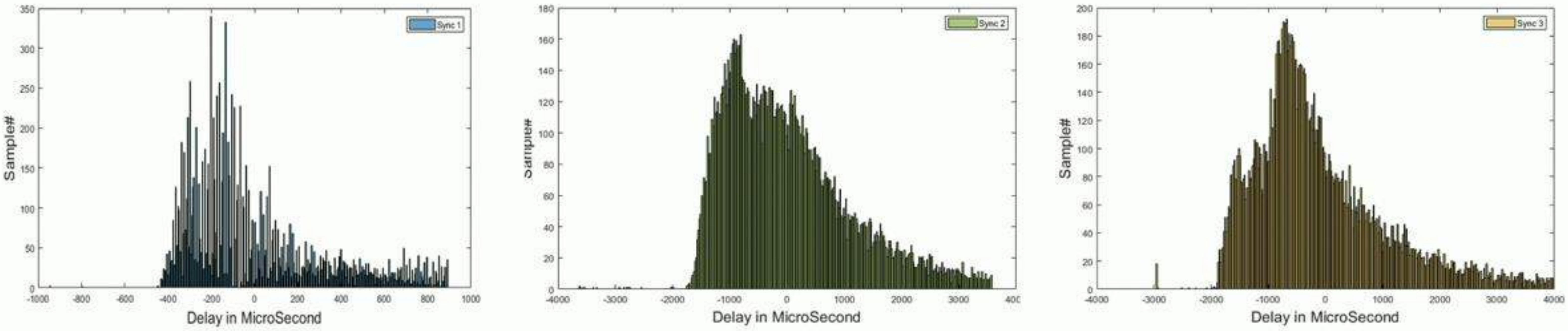

Std1: 0.55ms; Std2: 1.09ms; Std3: 1.40ms

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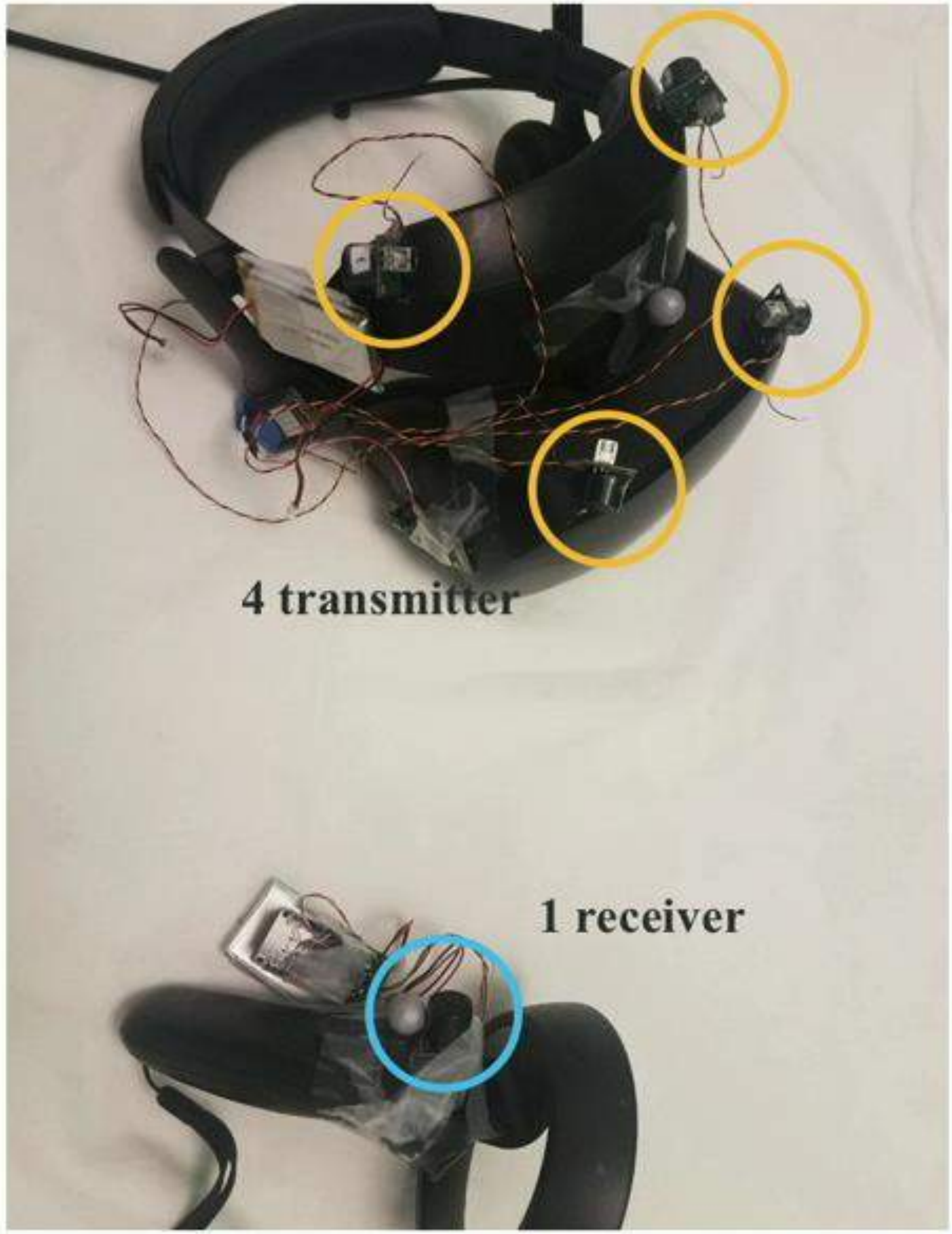

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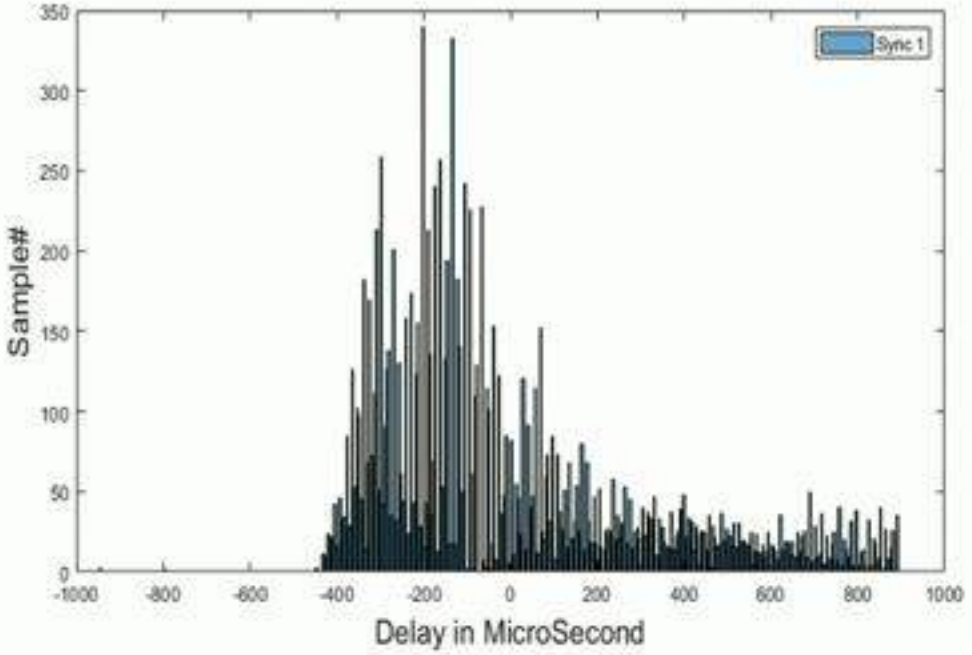

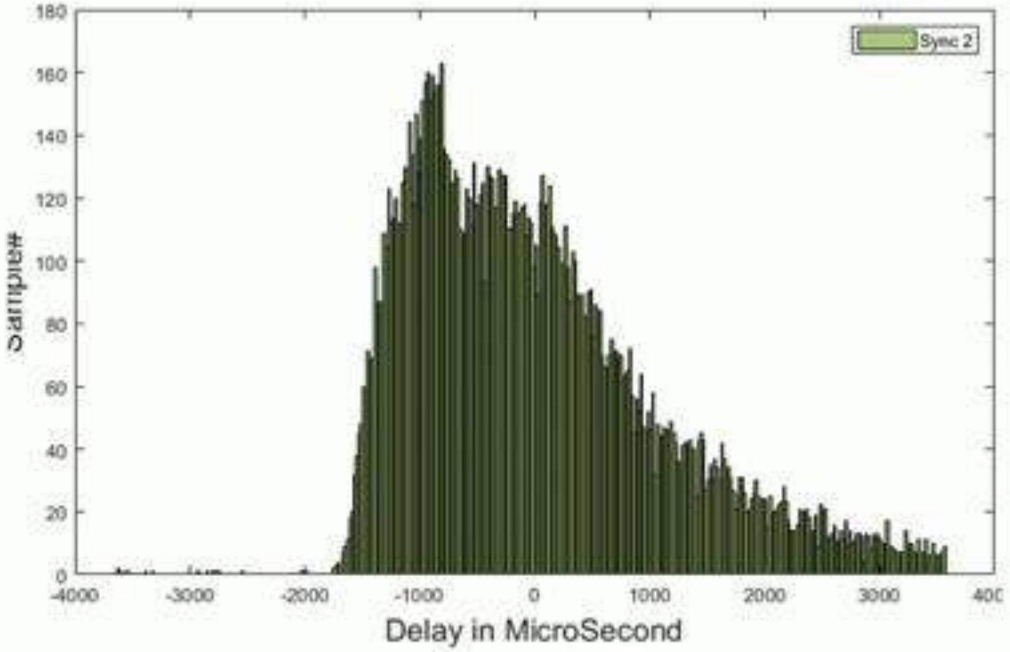

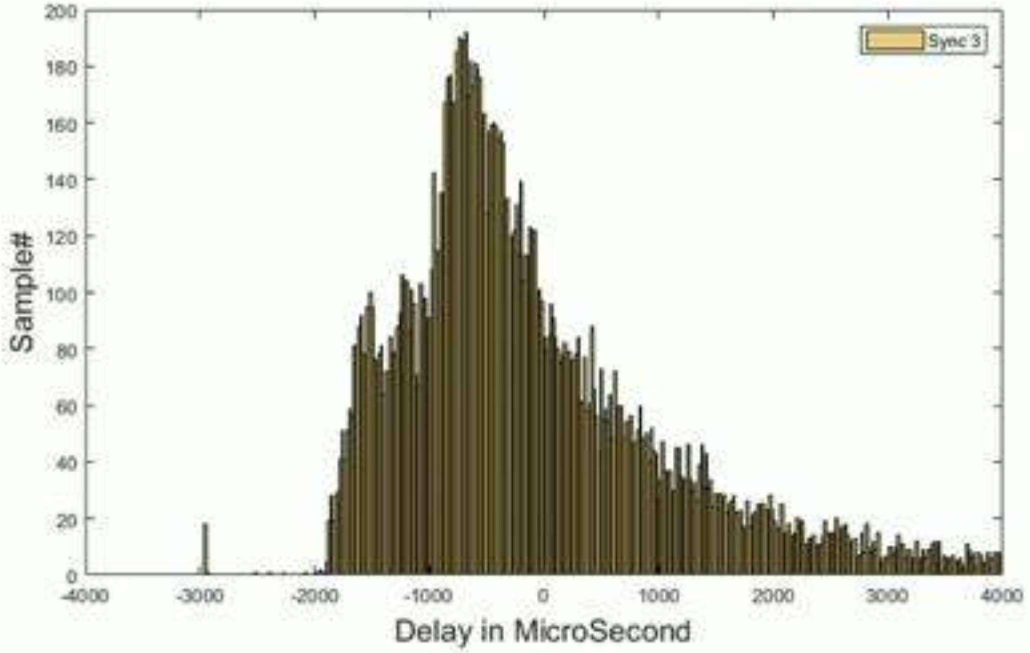

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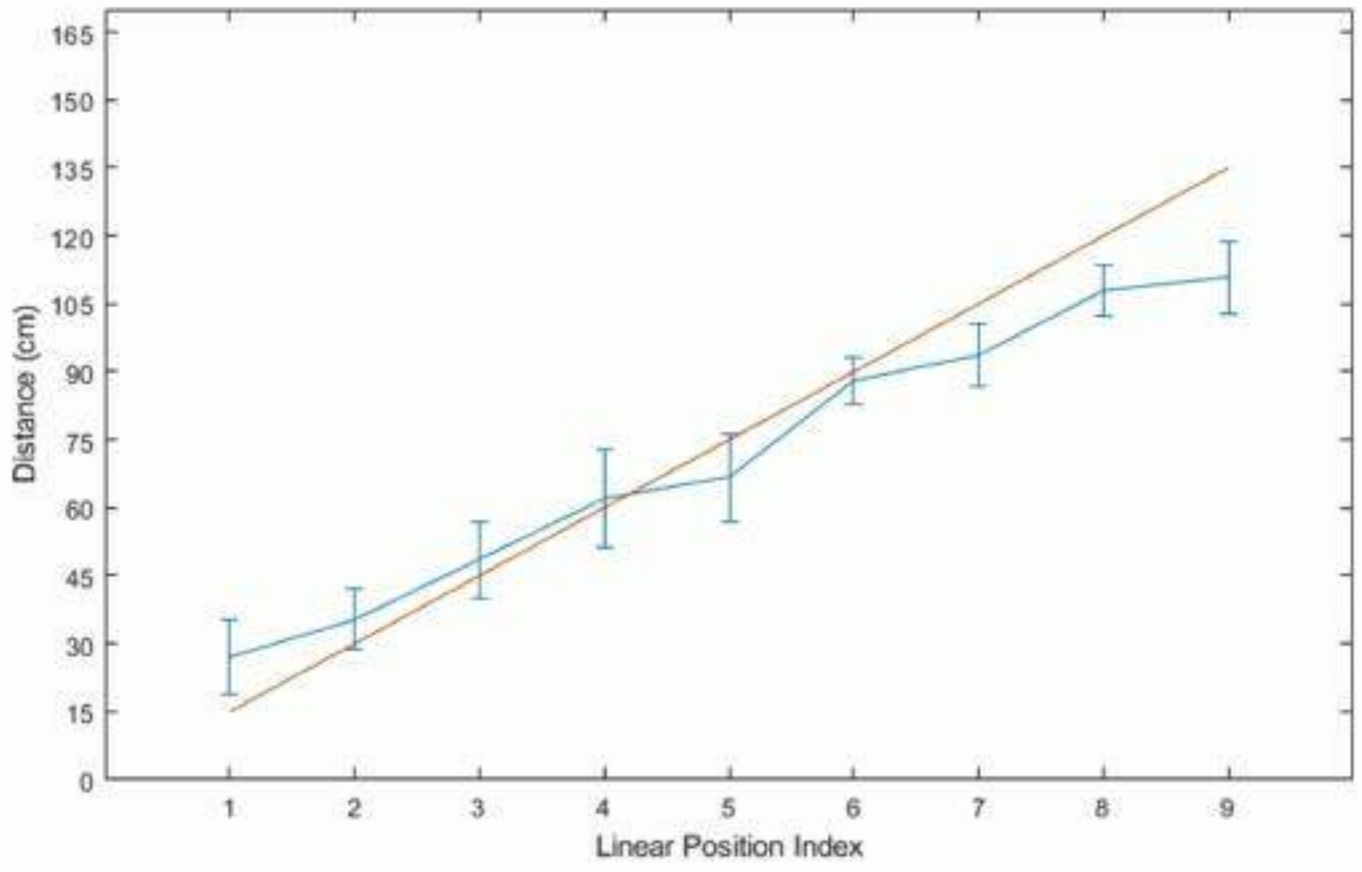
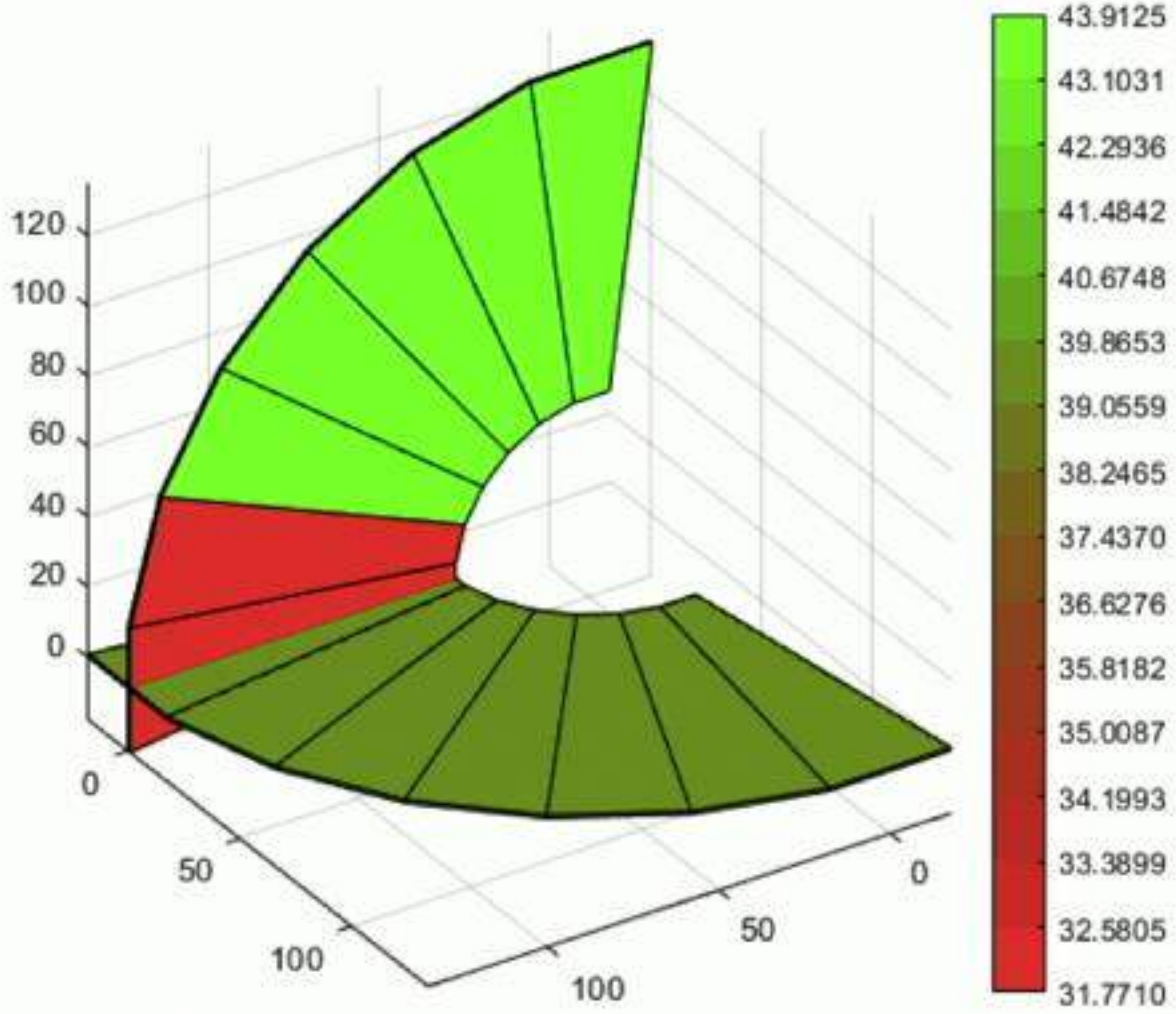
1. Lightweight Sensor for Ultrasound Ranging

- Tracking accuracy (distance and angle)





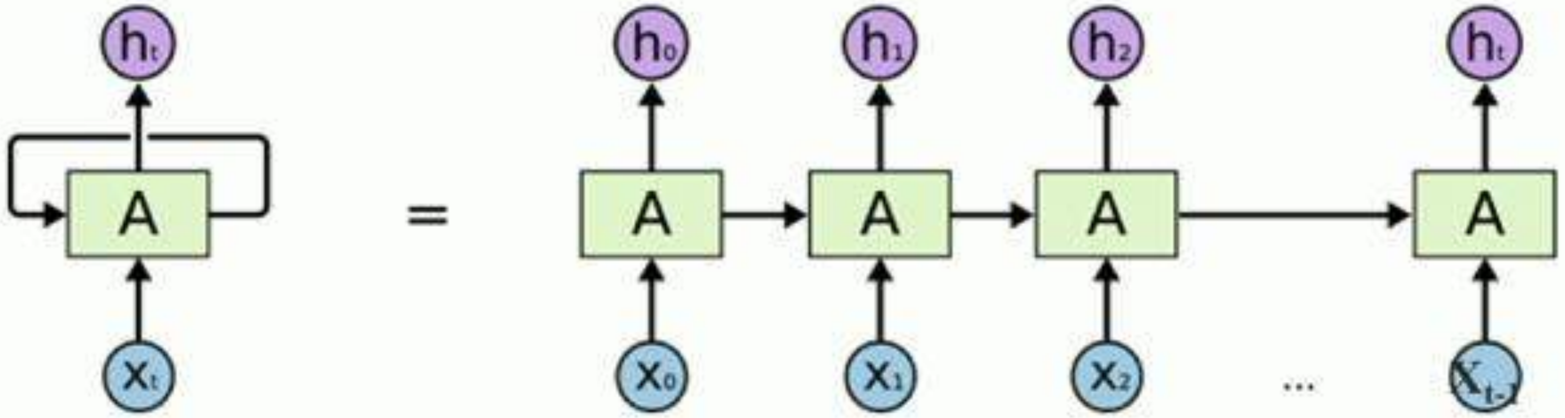
Average Distance Error: 9.74cm; Std:10.31cm

2. Learning-based Model for Tracking

- Autoregressive time-series forecasting model

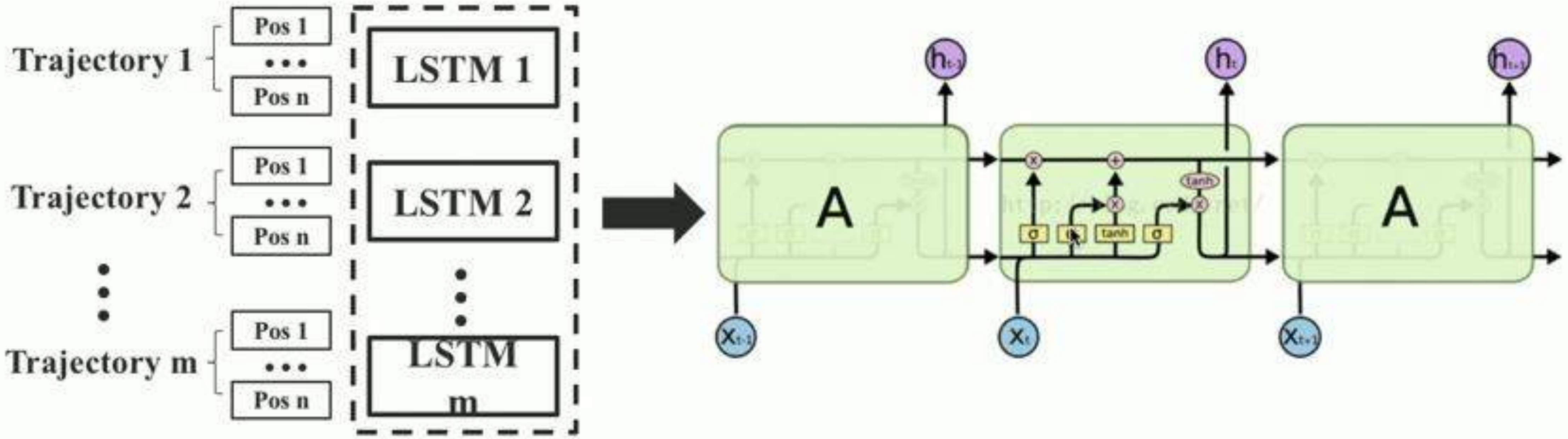
$$X_t = a_0 + a_1 X_{t-1} + a_2 X_{t-2} + \cdots + a_p X_{t-p} + \varepsilon_t, t \in \mathbb{Z} \qquad \{\varepsilon_t\} \in N(0,\sigma^2)$$

- Can also be learned using machine learning



2. Learning-based Model for Tracking

- RNNs: Natural model for tracking time-series data
- We use LSTMs to track time-series data



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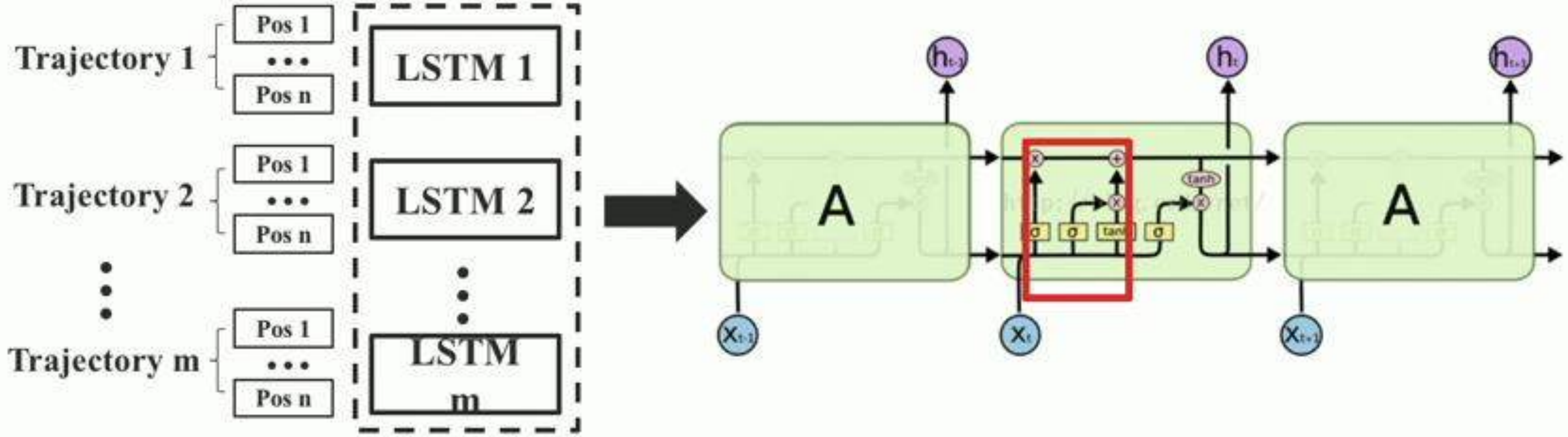

Forget Gate:

$$f_t = \sigma(W_f * [h_{t-1}, x_t] + b_f)$$

Input Gate:

$$i_t = \sigma(W_i * [h_{t-1}, x_t] + b_i)$$

$$\widetilde{C}_t = tanh(W_C * [h_{t-1}, x_t] + b_C)$$

$$C_t = f_t * C_{t-1} + i_t * \widetilde{C}_t$$

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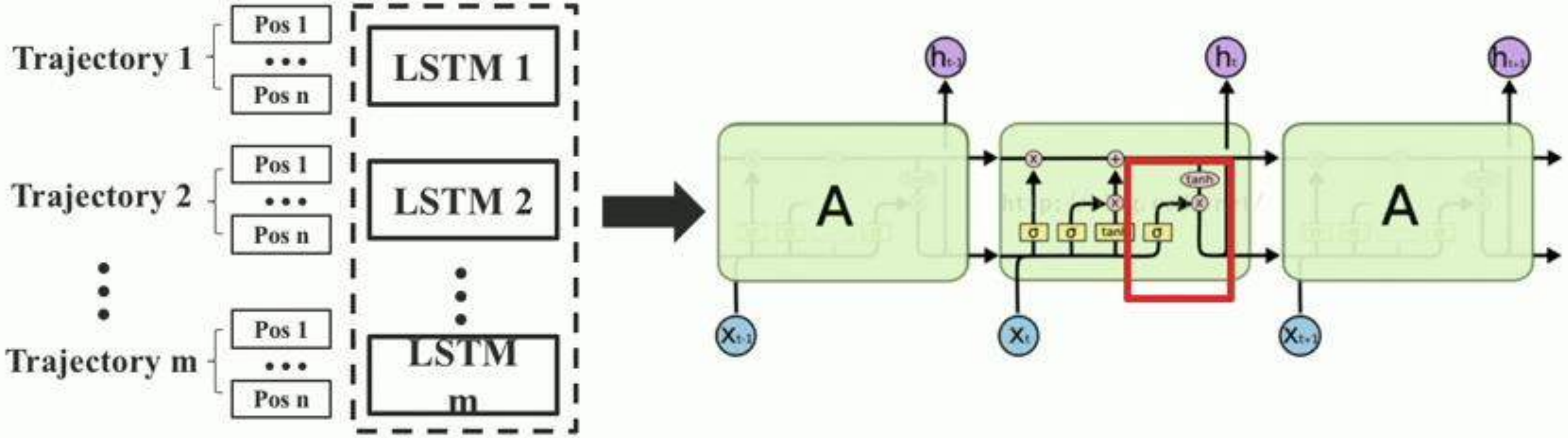

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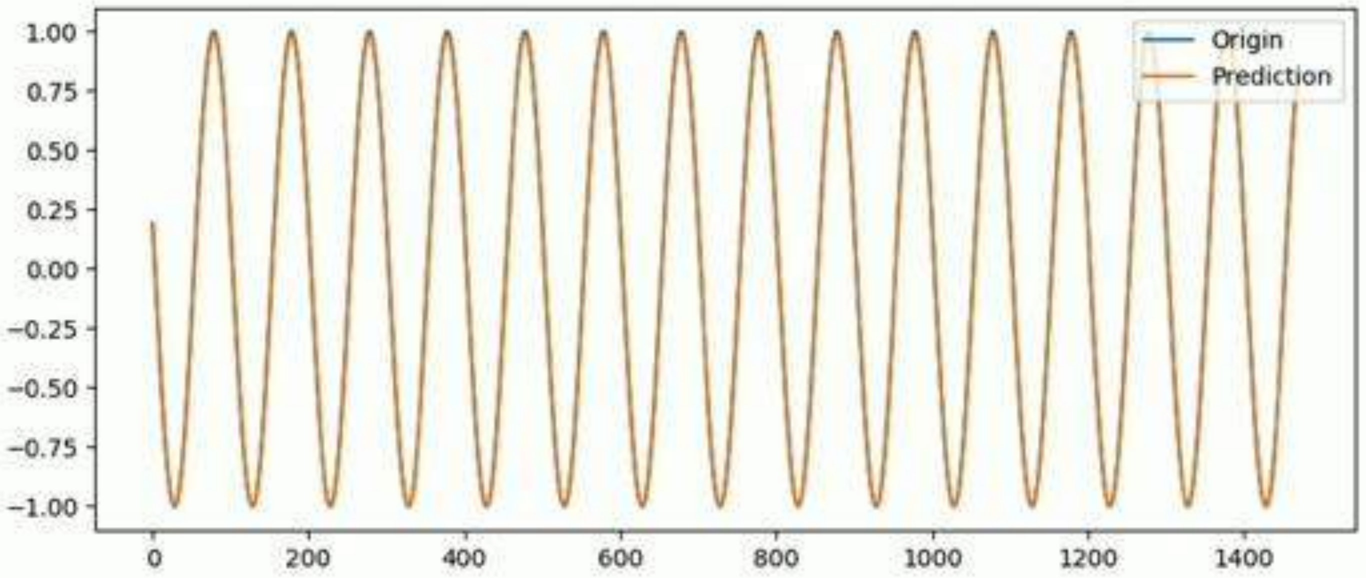
Output Gate:

$$o_t = \sigma(W_o * [h_{t-1}, x_t] + b_o)$$
$$h_t = o_t * \tanh(C_t)$$

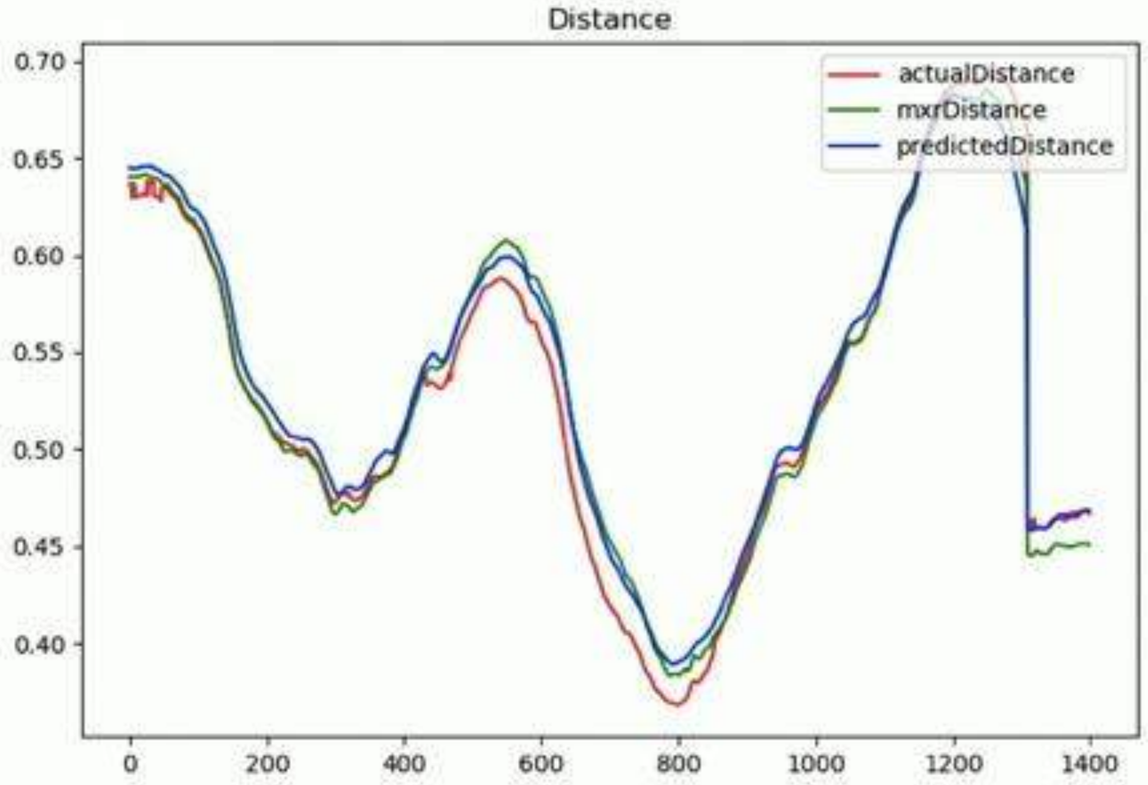
2. Learning-based Model for Tracking

- Tracking performance for Sinusoid and MXR data

Autoregression on sinusoid



Autoregression on MXR Data



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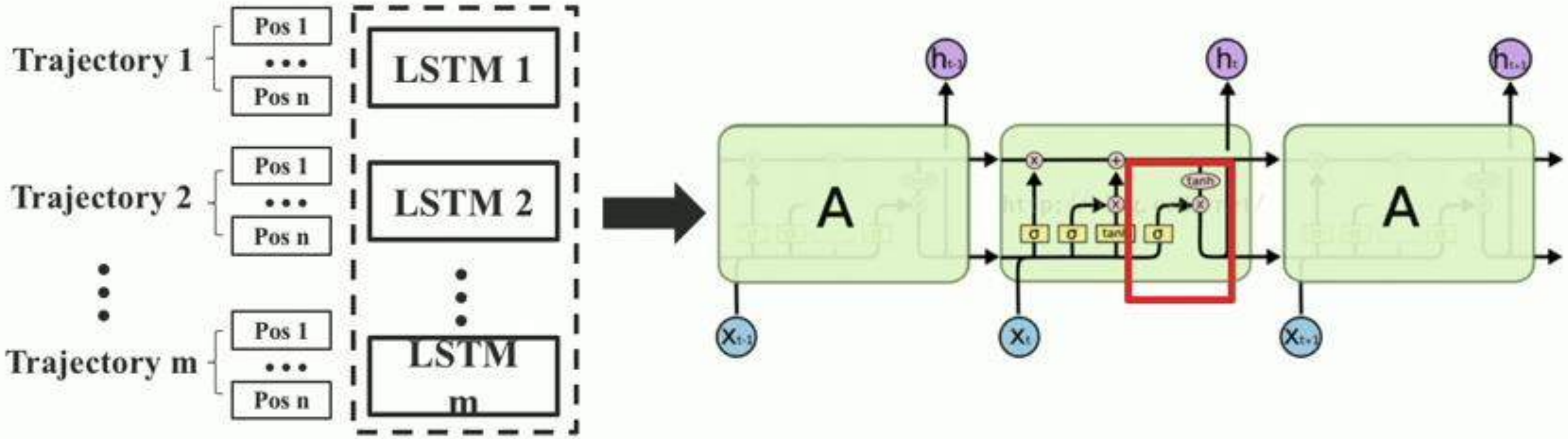

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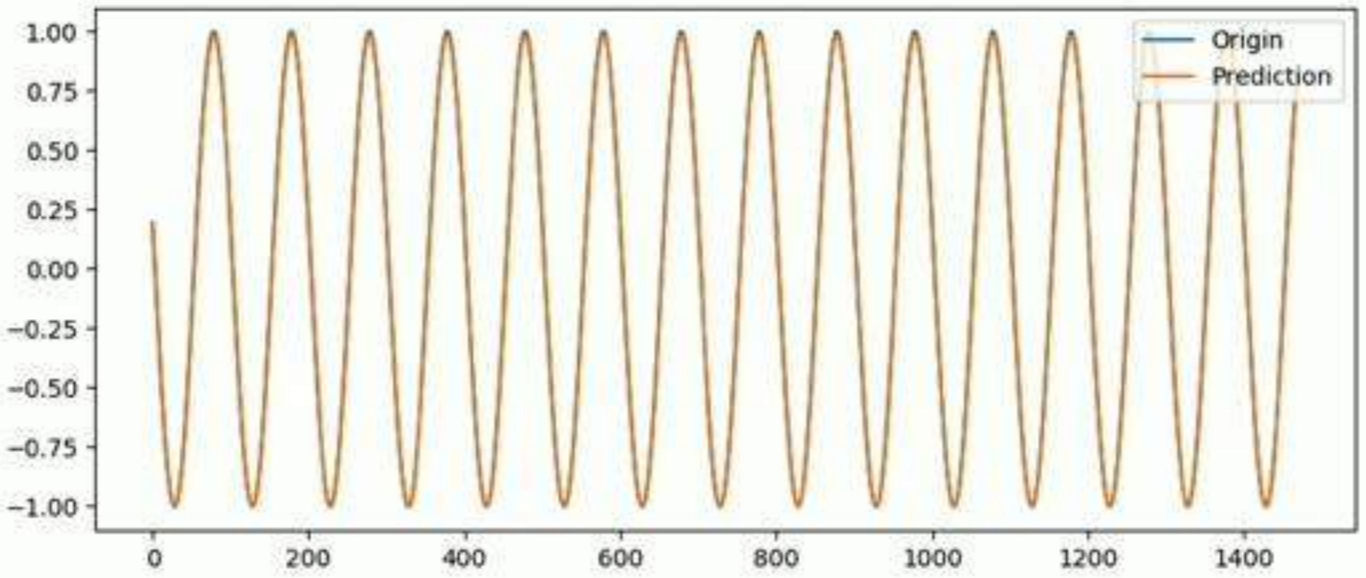
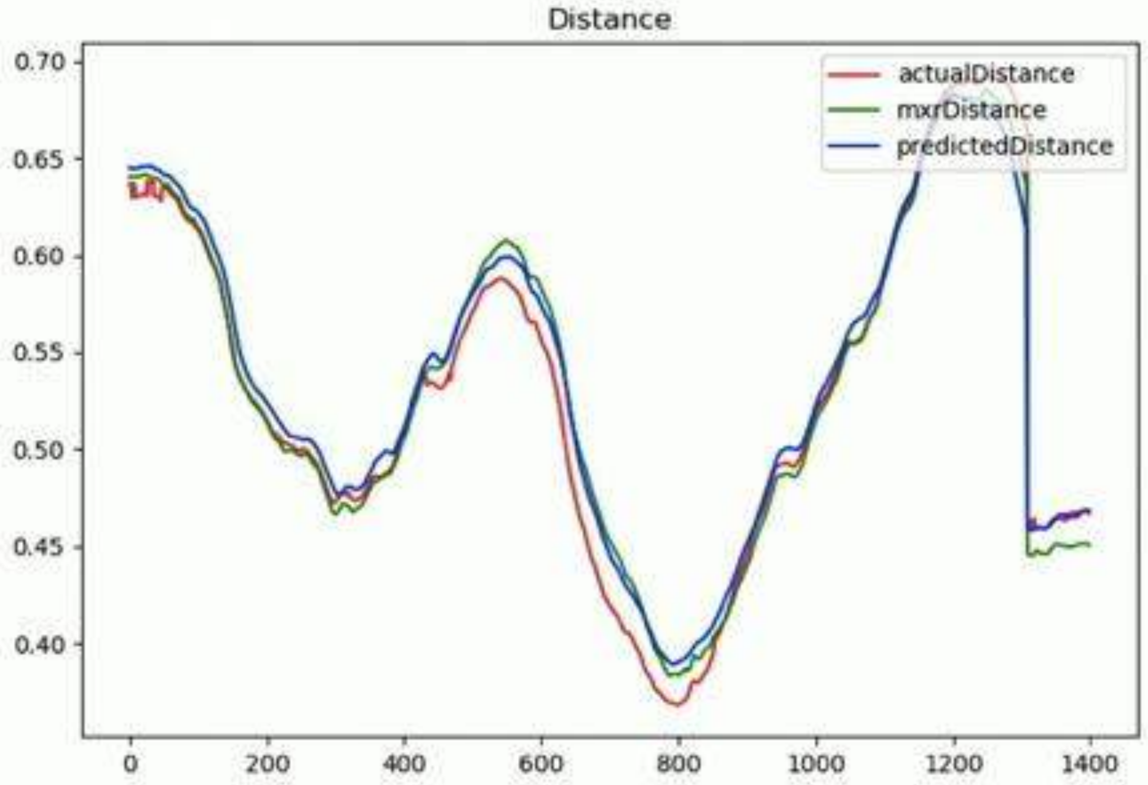


Autoregression on MXR Data



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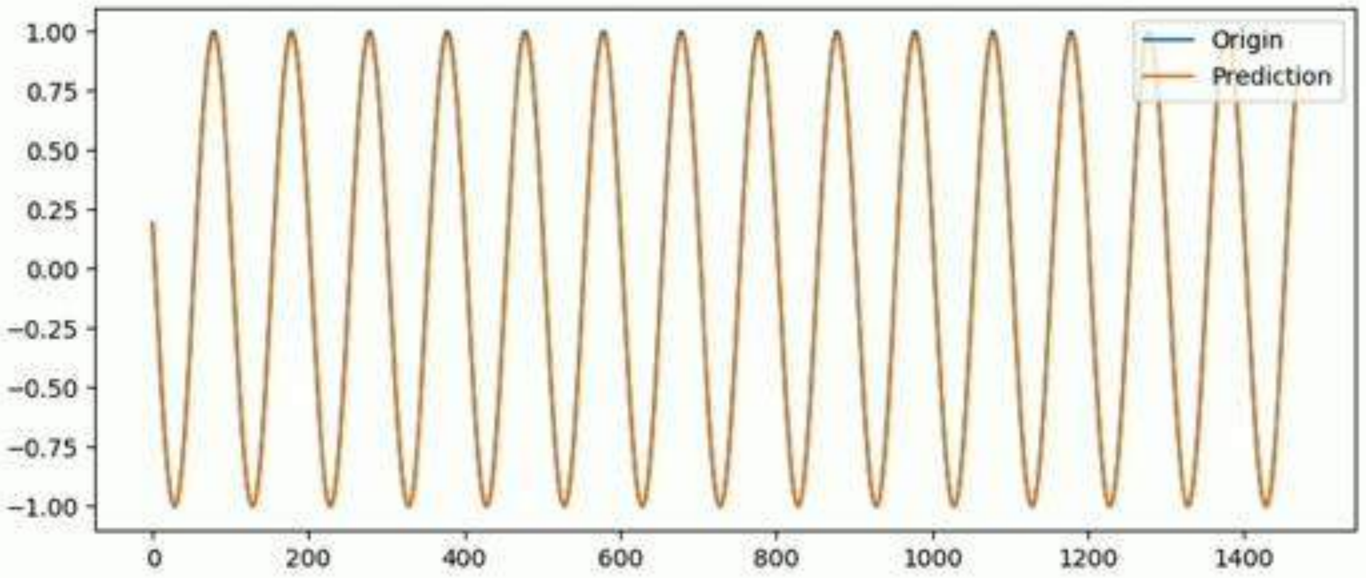

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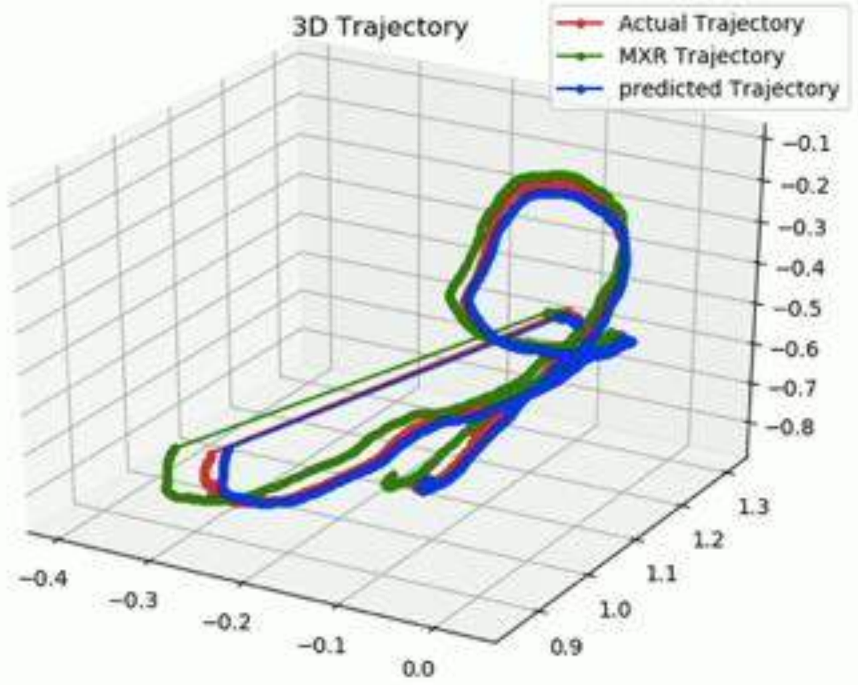
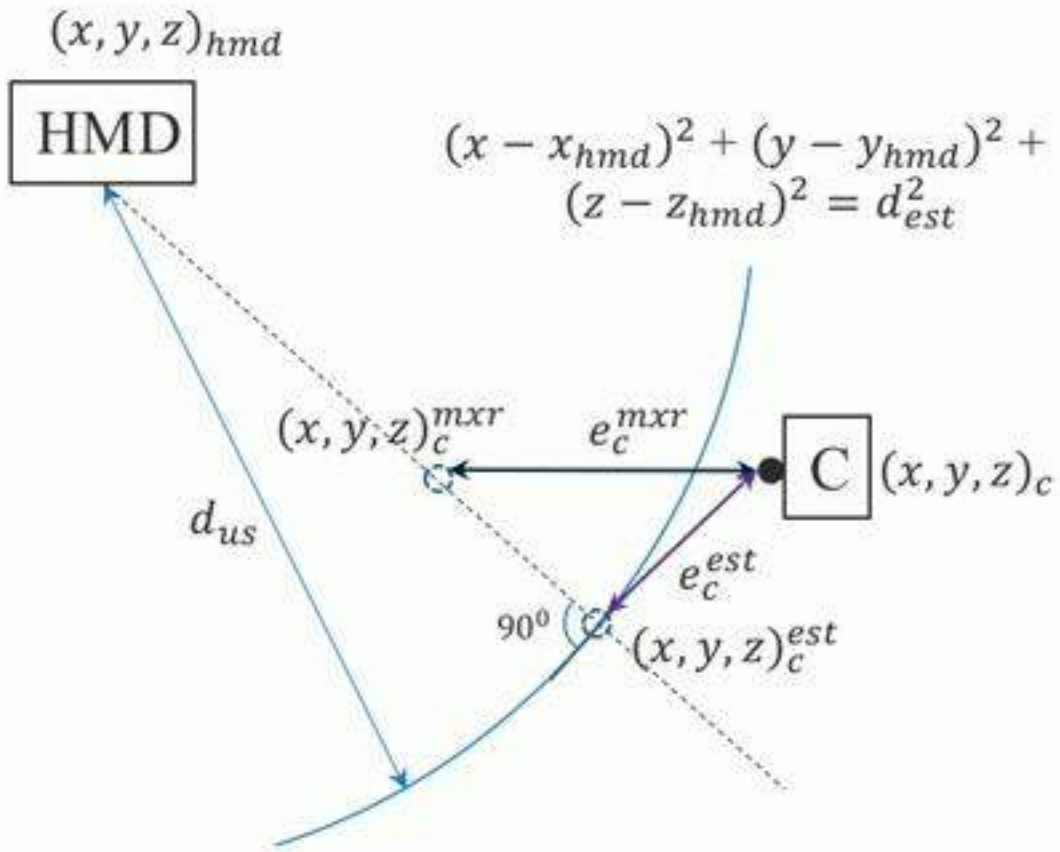


3. Data fusion System for Trajectory Tracking

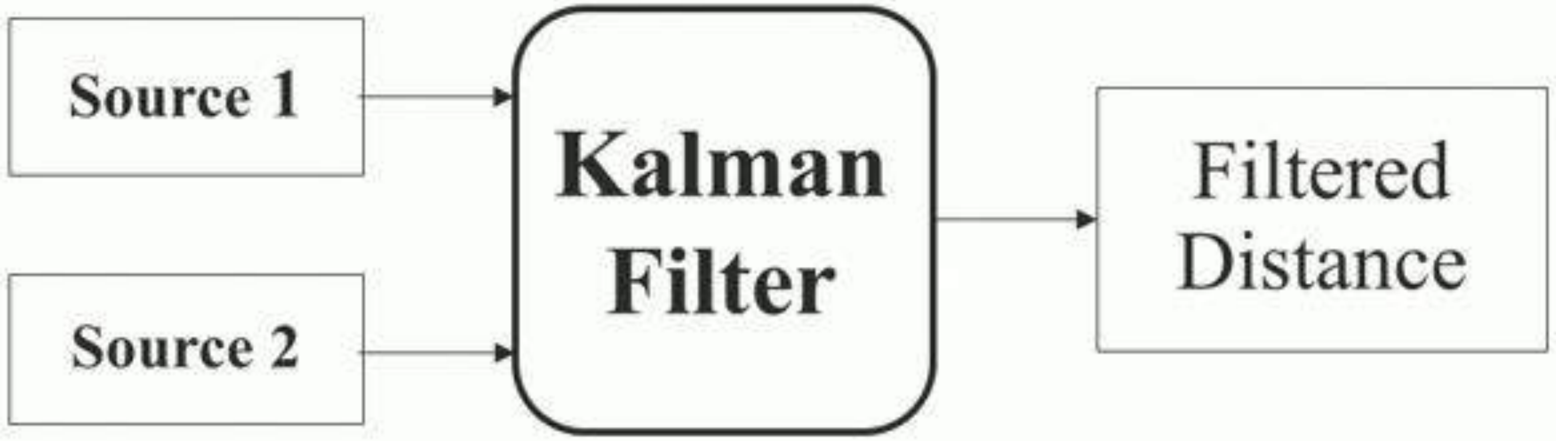
- Spherical Projection to get the estimated position



Given d_{est}, $(x, y, z)_c^{est} = \frac{d_{est}}{d} * [(x_c^{mxr} - x_{hmd}), (y_c^{mxr} - y_{hmd}), (z_c^{mxr} - z_{hmd})] + [x_{hmd}, y_{hmd}, z_{hmd}]$

3. Data fusion System for Trajectory Tracking

- How to get the d_{est}
  - Source 1: Ultrasound ranging
  - Source 2: LSTM model/MXR



Kalman Filter

- Predict: $\hat{\mathbf{x}}_{k|k-1} = \mathbf{F}_k \hat{\mathbf{x}}_{k-1|k-1} + \mathbf{B}_k \mathbf{u}_k$

  $\mathbf{P}_{k|k-1} = \mathbf{F}_k \mathbf{P}_{k-1|k-1} \mathbf{F}_k^{\mathrm{T}} + \mathbf{Q}_k$

- Update: $\tilde{\mathbf{y}}_k = \mathbf{z}_k - \mathbf{H}_k \hat{\mathbf{x}}_{k|k-1}$

  $\mathbf{S}_k = \mathbf{R}_k + \mathbf{H}_k \mathbf{P}_{k|k-1} \mathbf{H}_k^{\mathrm{T}}$

  $\mathbf{K}_k = \mathbf{P}_{k|k-1} \mathbf{H}_k^{\mathrm{T}} \mathbf{S}_k^{-1}$

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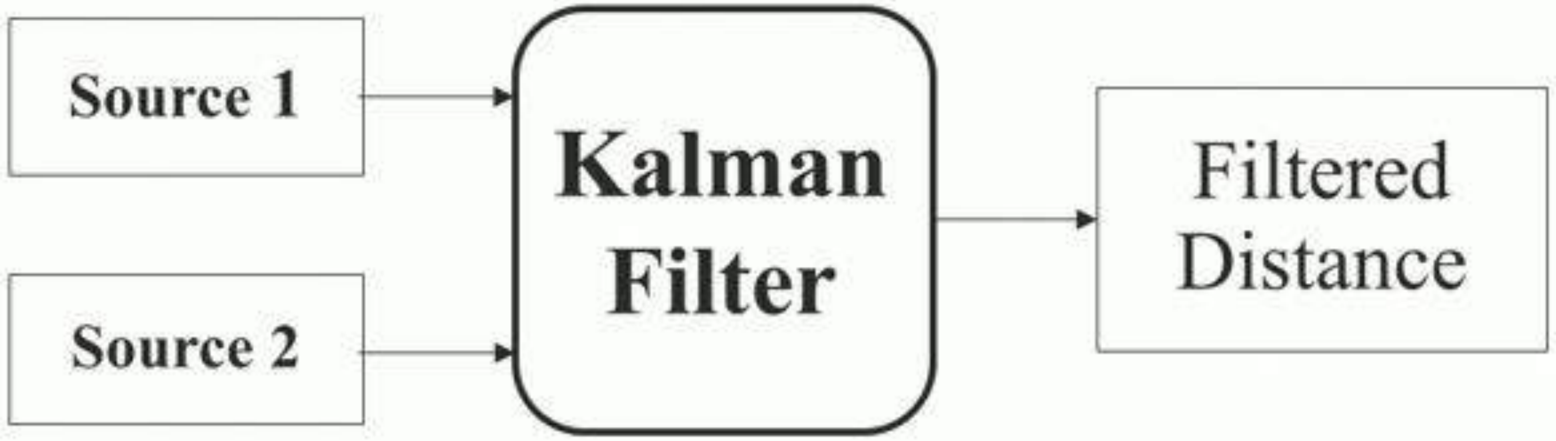

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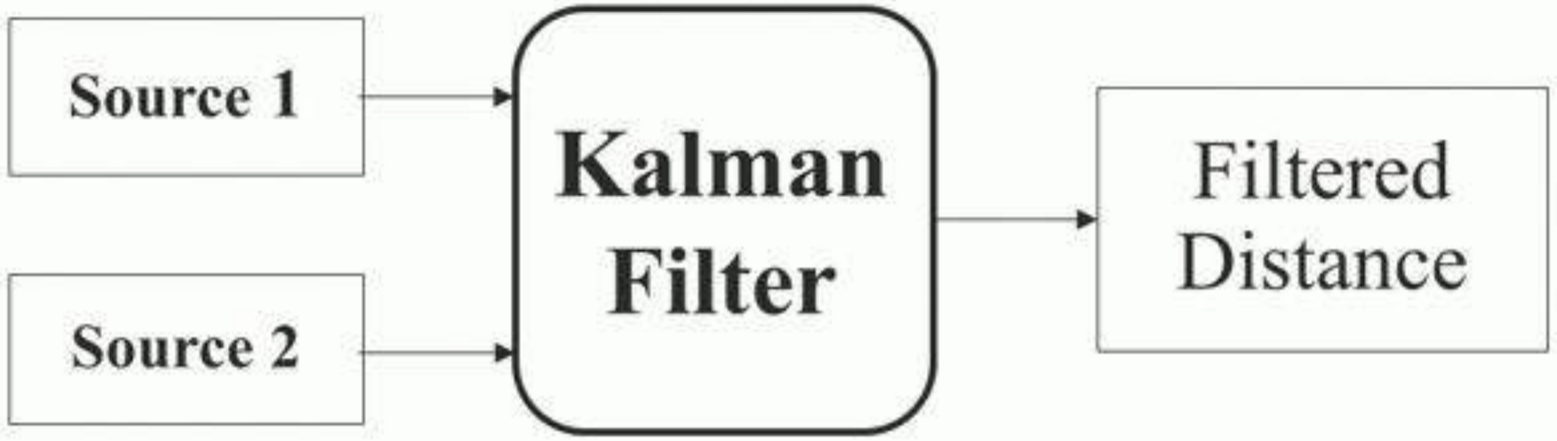

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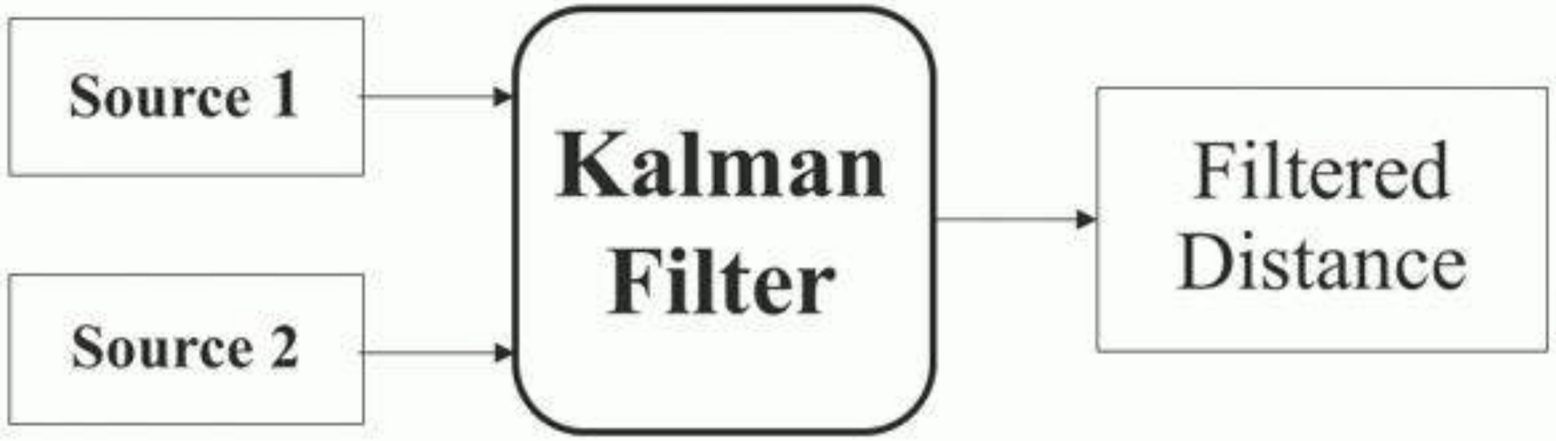

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  $\hat{\mathbf{x}}_{k|k} = \hat{\mathbf{x}}_{k|k-1} + \mathbf{K}_k \tilde{\mathbf{y}}_k$

  $\mathbf{P}_{k|k} = (\mathbf{I} - \mathbf{K}_k \mathbf{H}_k) \mathbf{P}_{k|k-1} (\mathbf{I} - \mathbf{K}_k \mathbf{H}_k)^T + \mathbf{K}_k \mathbf{R}_k \mathbf{K}_k^T$

  $\tilde{\mathbf{y}}_{k|k} = \mathbf{z}_k - \mathbf{H}_k \hat{\mathbf{x}}_{k|k}$

3. Data fusion System for Trajectory Tracking

- Pipeline

Tracking Status (every 20ms)

2	**1**	**2**	**1**	**1**	**1**	**1**	**…**	**2**	**2**	**2**

MXR Prediction (every 20ms)

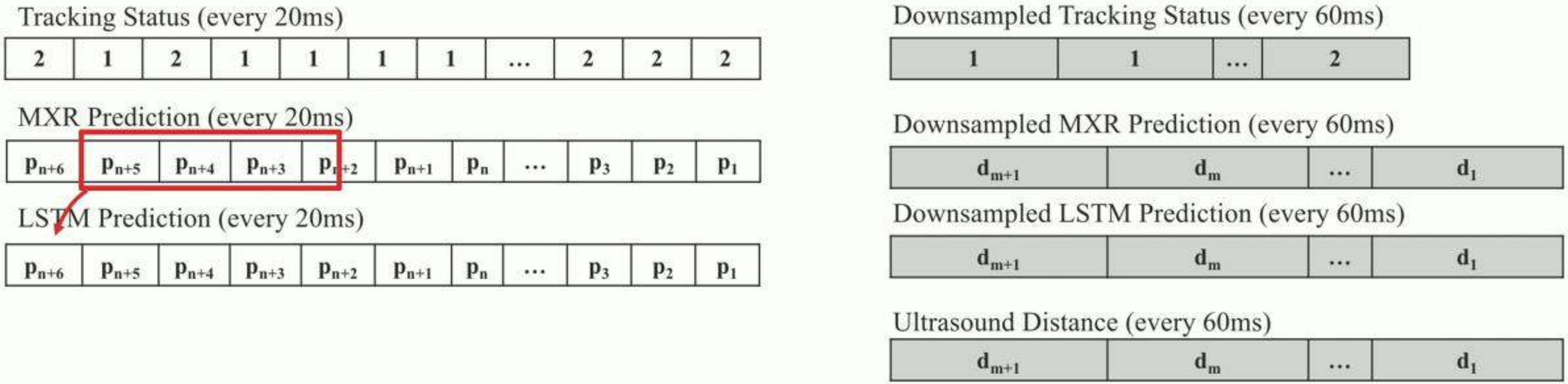
p_{n+6}	p_{n+5}	p_{n+4}	p_{n+3}	p_{n+2}	p_{n+1}	p_n	…	p_3	p_2	p_1

LSTM Prediction (every 20ms)

p_{n+6}	p_{n+5}	p_{n+4}	p_{n+3}	p_{n+2}	p_{n+1}	p_n	…	p_3	p_2	p_1

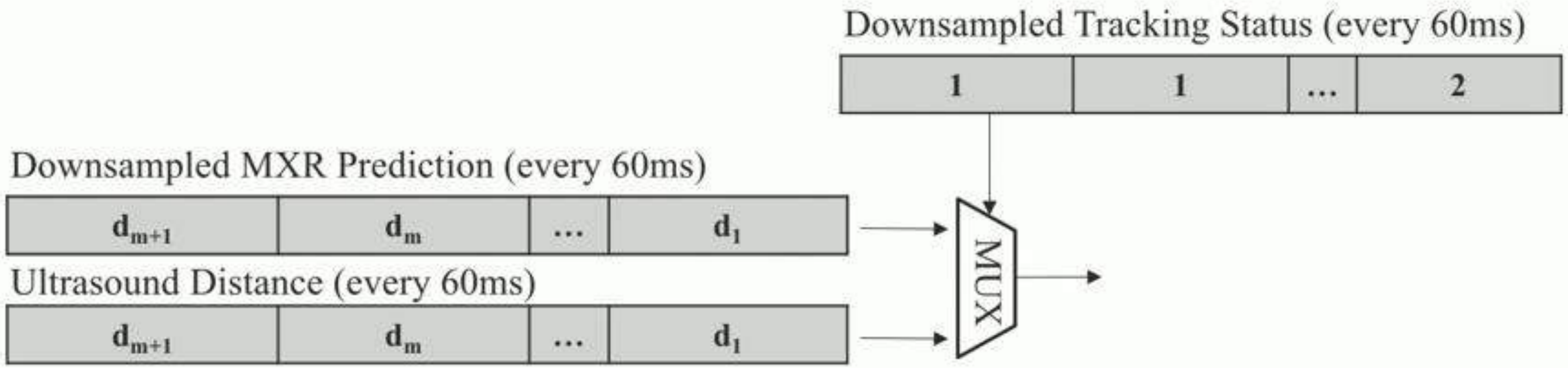
3. Data fusion System for Trajectory Tracking

- Pipeline



3. Data fusion System for Trajectory Tracking

- Pipeline



3. Data fusion System for Trajectory Tracking

- Pipeline

Tracking Status (every 20ms)

2	1	2	1	1	1	1	…	2	2	2

MXR Prediction (every 20ms)

p_{n+6}	p_{n+5}	p_{n+4}	p_{n+3}	p_{n+2}	p_{n+1}	p_n	…	p_3	p_2	p_1

LSTM Prediction (every 20ms)

p_{n+6}	p_{n+5}	p_{n+4}	p_{n+3}	p_{n+2}	p_{n+1}	p_n	…	p_3	p_2	p_1

Downsampled Tracking Status (every 60ms)

1	1	…	2

Downsampled MXR Prediction (every 60ms)

d_{m+1}	d_m	…	d_1

Downsampled LSTM Prediction (every 60ms)

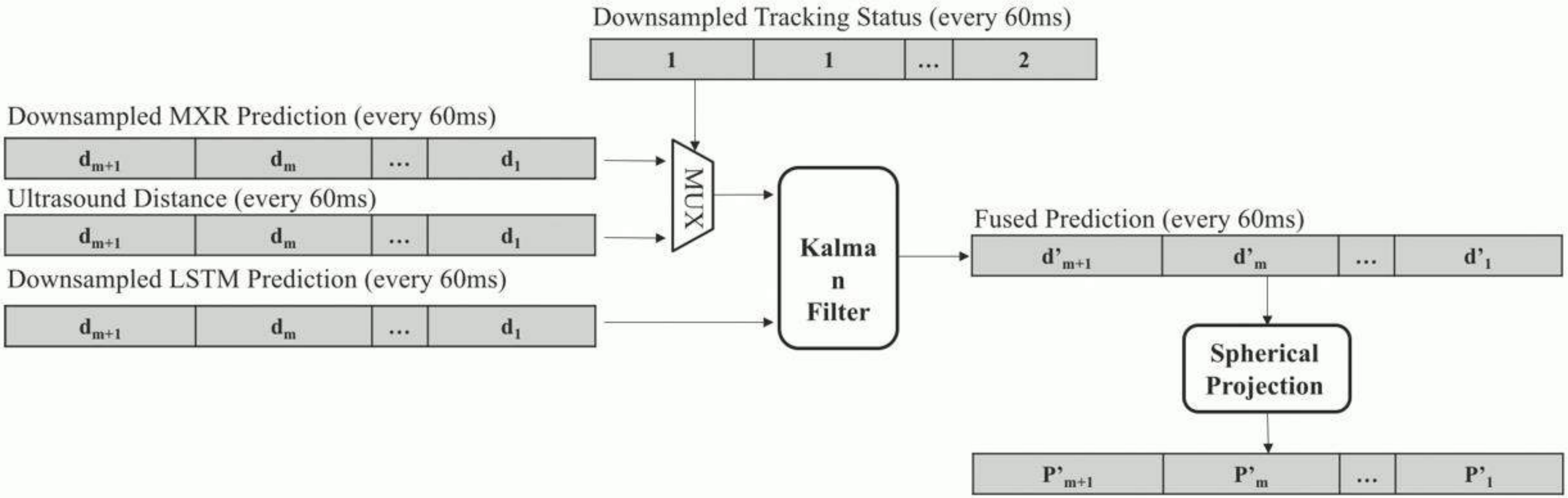
d_{m+1}	d_m	…	d_1

Ultrasound Distance (every 60ms)

d_{m+1}	d_m	…	d_1

3. Data fusion System for Trajectory Tracking

- Pipeline



3. Data fusion System for Trajectory Tracking

- Pipeline

Tracking Status (every 20ms)

2	1	2	1	1	1	1	…	2	2	2

MXR Prediction (every 20ms)

p_{n+6}	p_{n+5}	p_{n+4}	p_{n+3}	p_{n+2}	p_{n+1}	p_n	…	p_3	p_2	p_1

LSTM Prediction (every 20ms)

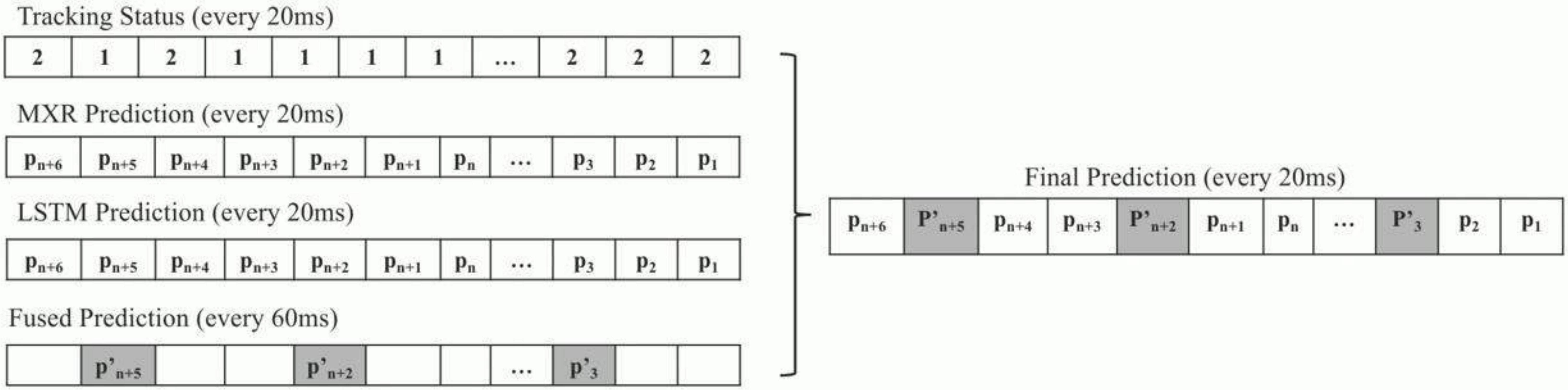
p_{n+6}	p_{n+5}	p_{n+4}	p_{n+3}	p_{n+2}	p_{n+1}	p_n	…	p_3	p_2	p_1

Fused Prediction (every 60ms)

	p'_{n+5}			p'_{n+2}			…	p'_3		

3. Data fusion System for Trajectory Tracking

- Pipeline



3. Data fusion System for Trajectory Tracking

- Offset-based Correction

Tracking Status (every 20ms)

2	1	2	1	1	1	1	…	2	2	2

MXR Prediction (every 20ms)

p_{n+6}	p_{n+5}	p_{n+4}	p_{n+3}	p_{n+2}	p_{n+1}	p_n	…	p_3	p_2	p_1

LSTM Prediction (every 20ms)

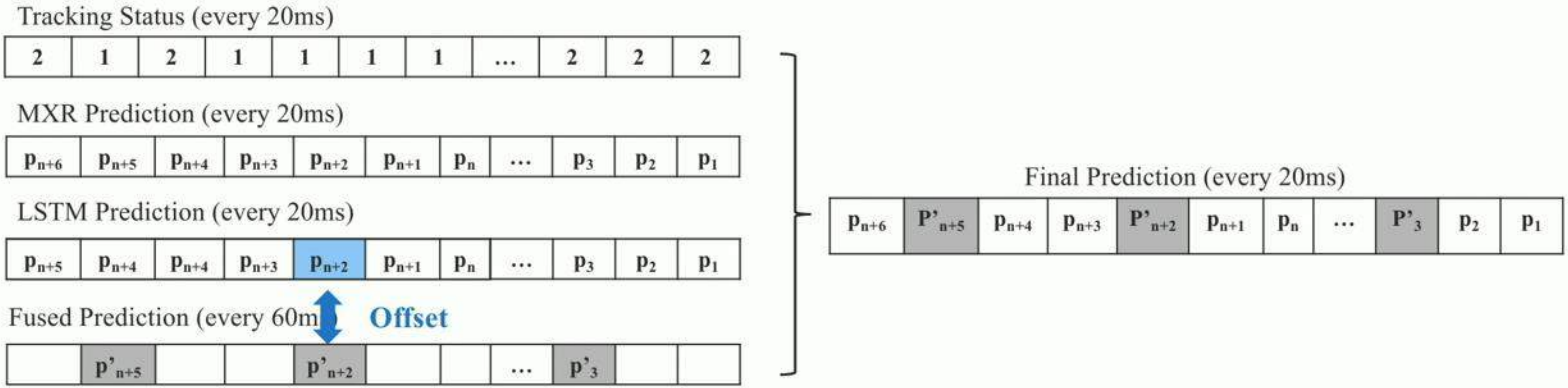
p_{n+6}	p_{n+5}	p_{n+4}	p_{n+3}	p_{n+2}	p_{n+1}	p_n	…	p_3	p_2	p_1

Fused Prediction (every 60ms)

	p'_{n+5}			p'_{n+2}			…	p'_3		

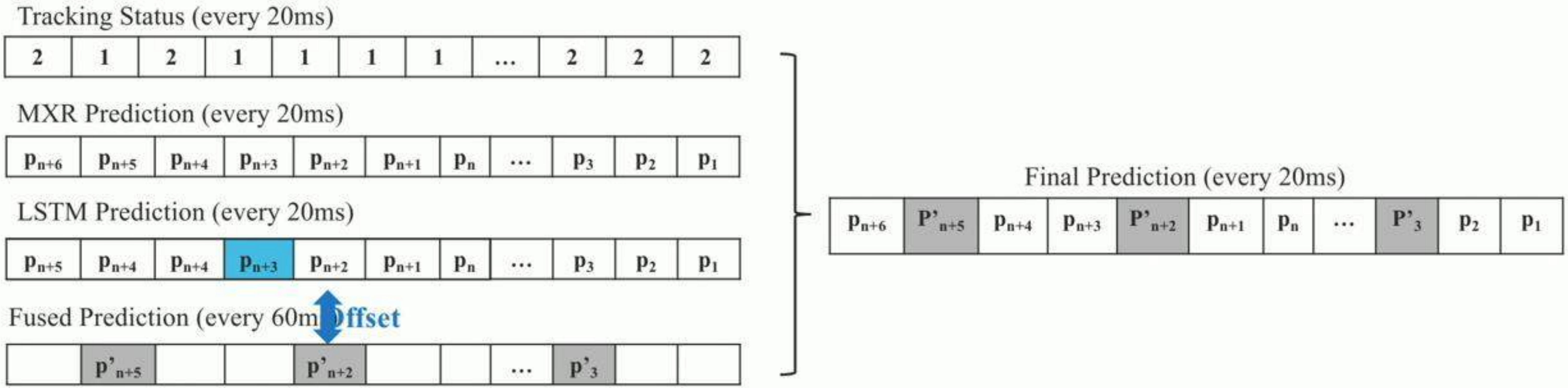
3. Data fusion System for Trajectory Tracking

- Offset-based Correction



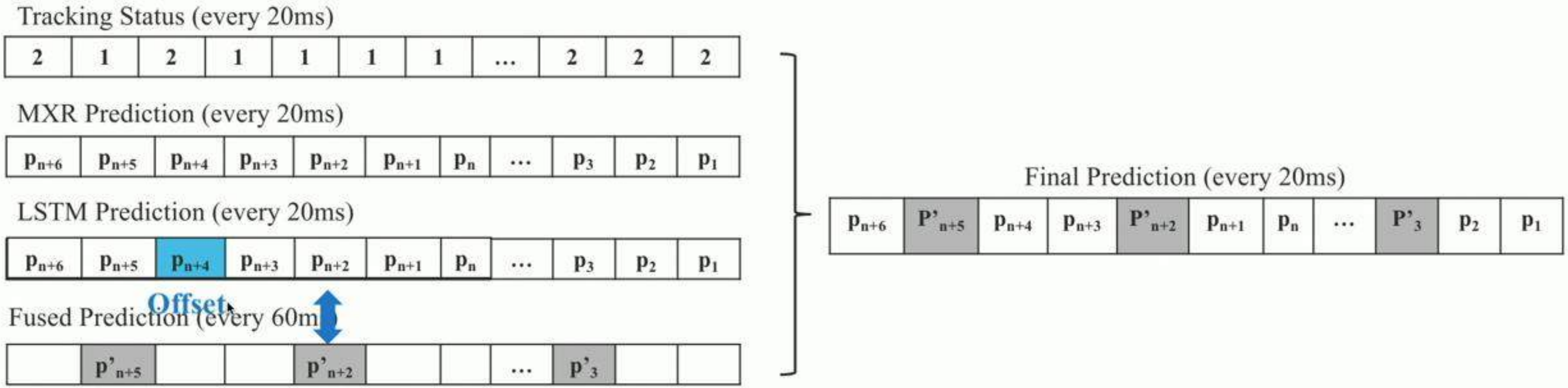
3. Data fusion System for Trajectory Tracking

- Offset-based Correction

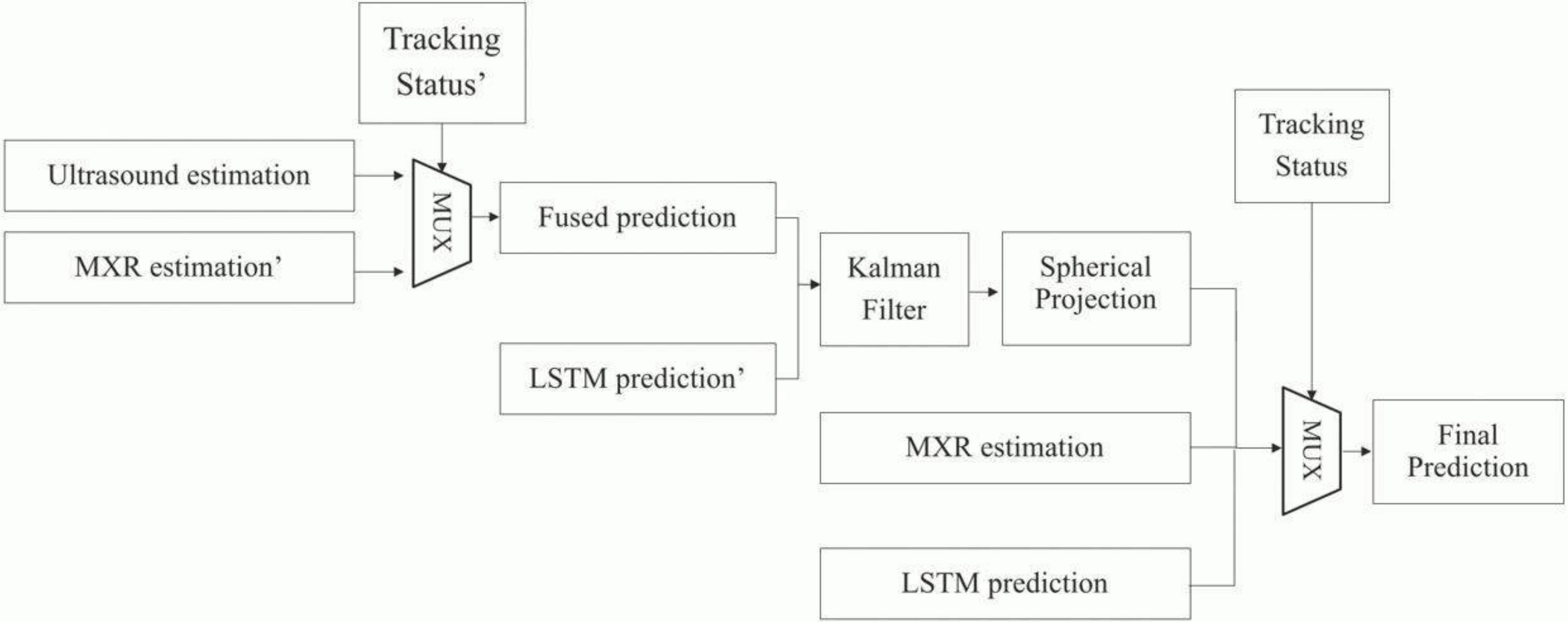


3. Data fusion System for Trajectory Tracking

- Offset-based Correction

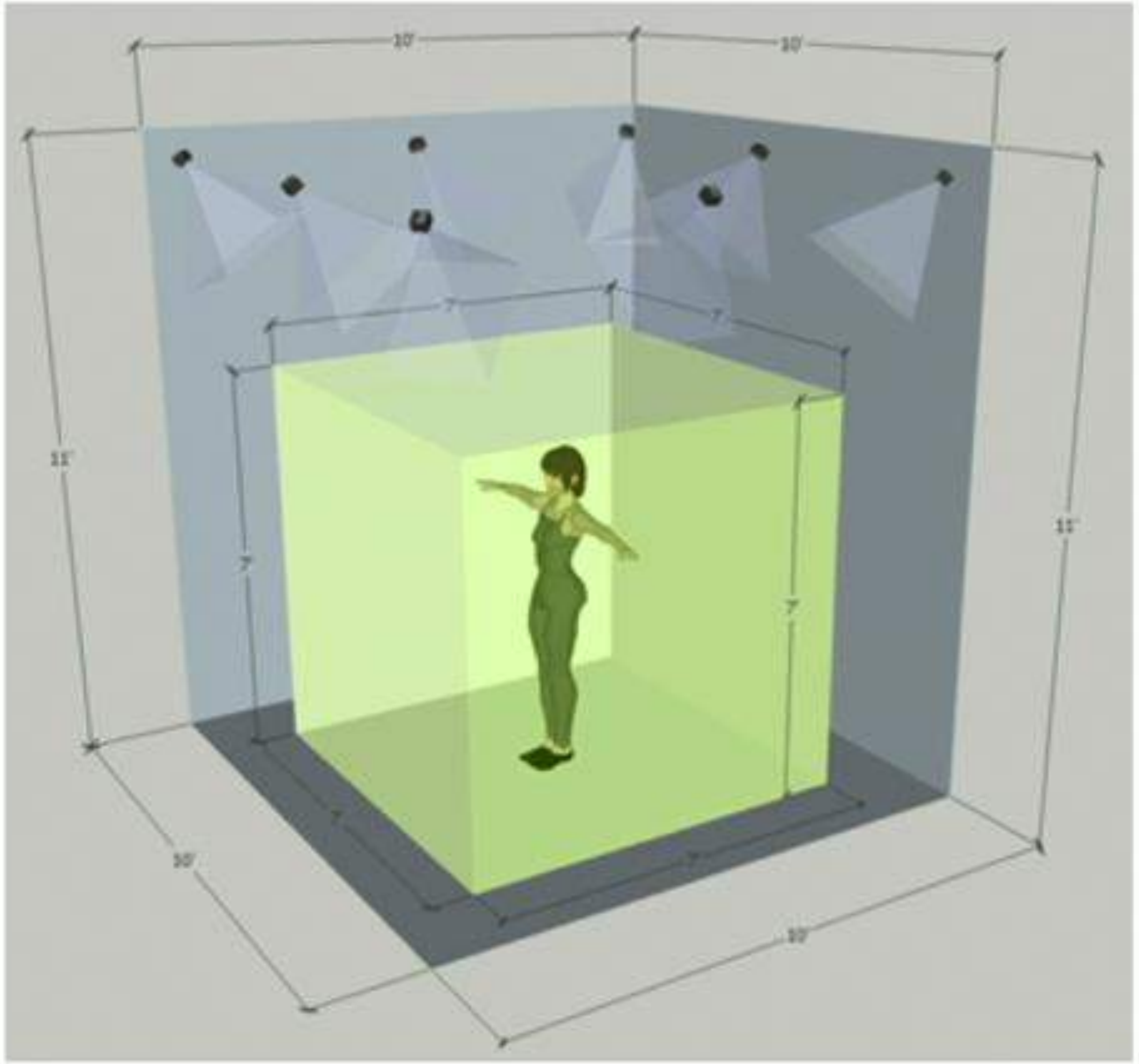


3. Data fusion System for Trajectory Tracking



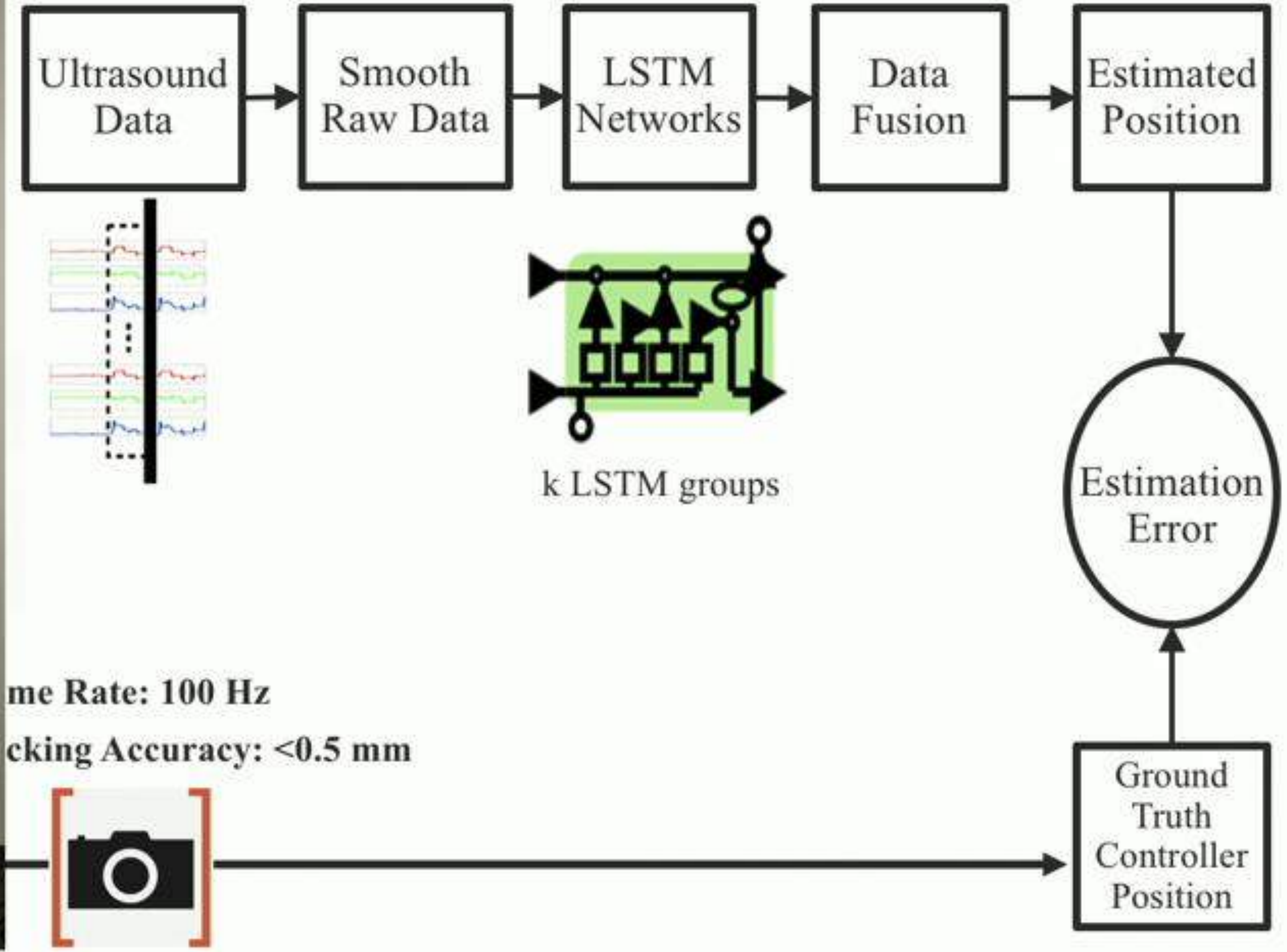
Data Collection Setup

- Motion capture
  - 8-camera OptiTrack, Windows Mixed Reality, in-FOV tracking
- Additional Information
  - Ultrasound Sensor, NN-based Model



Flex 3, OptiTrack System

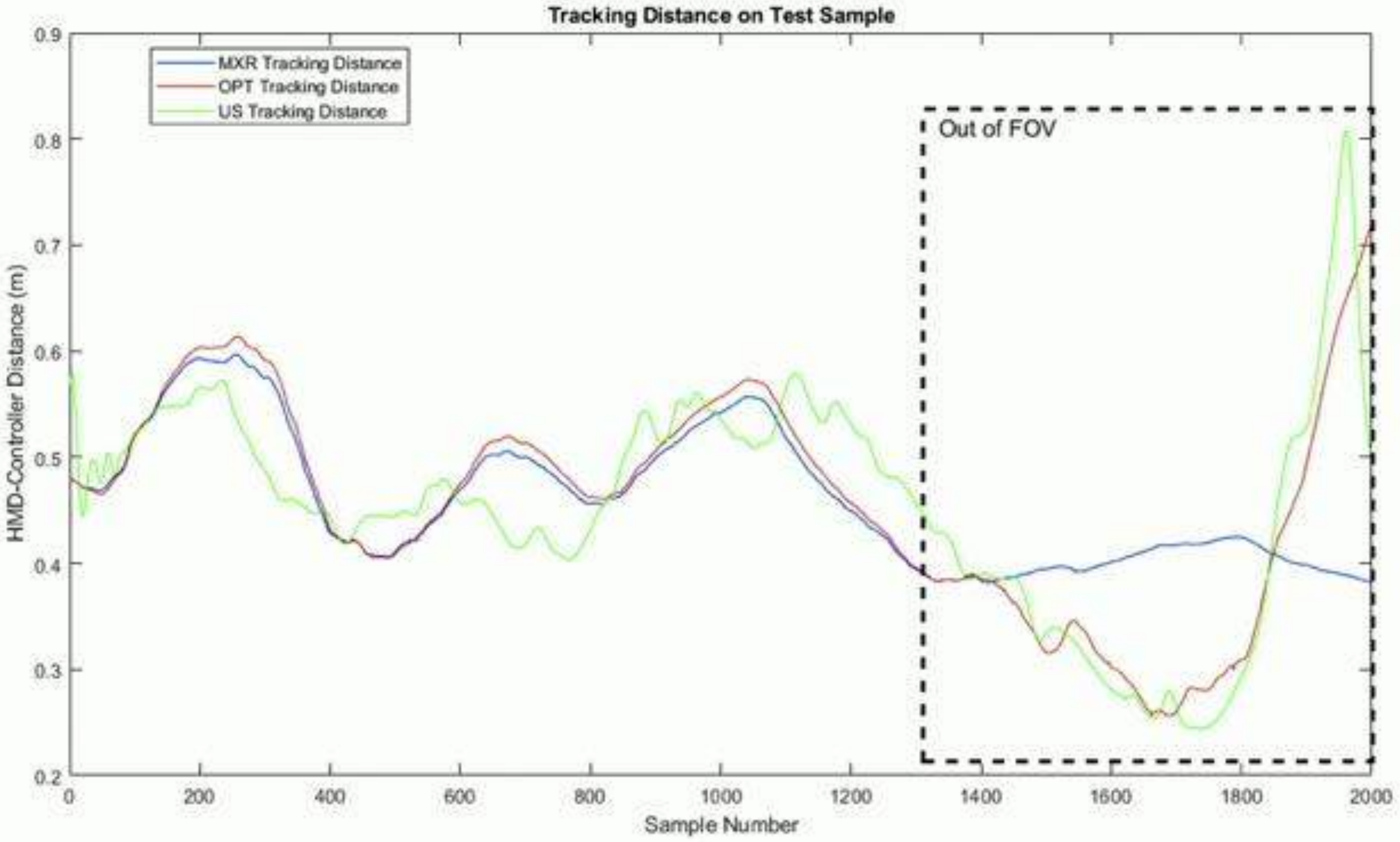
Data Collection Framework



Dataset	
Total no. trials	10
Avg. length of each trial	12 mins
Total length of data	2 hours
Ultrasound sampling freq.	60 Hz
OptiTrack sampling freq.	100 Hz
Mixed reality sampling freq.	50-60 Hz
Ground truth collection	8 Flex3 Camera + Motive 2.0.2

Tracking Performance

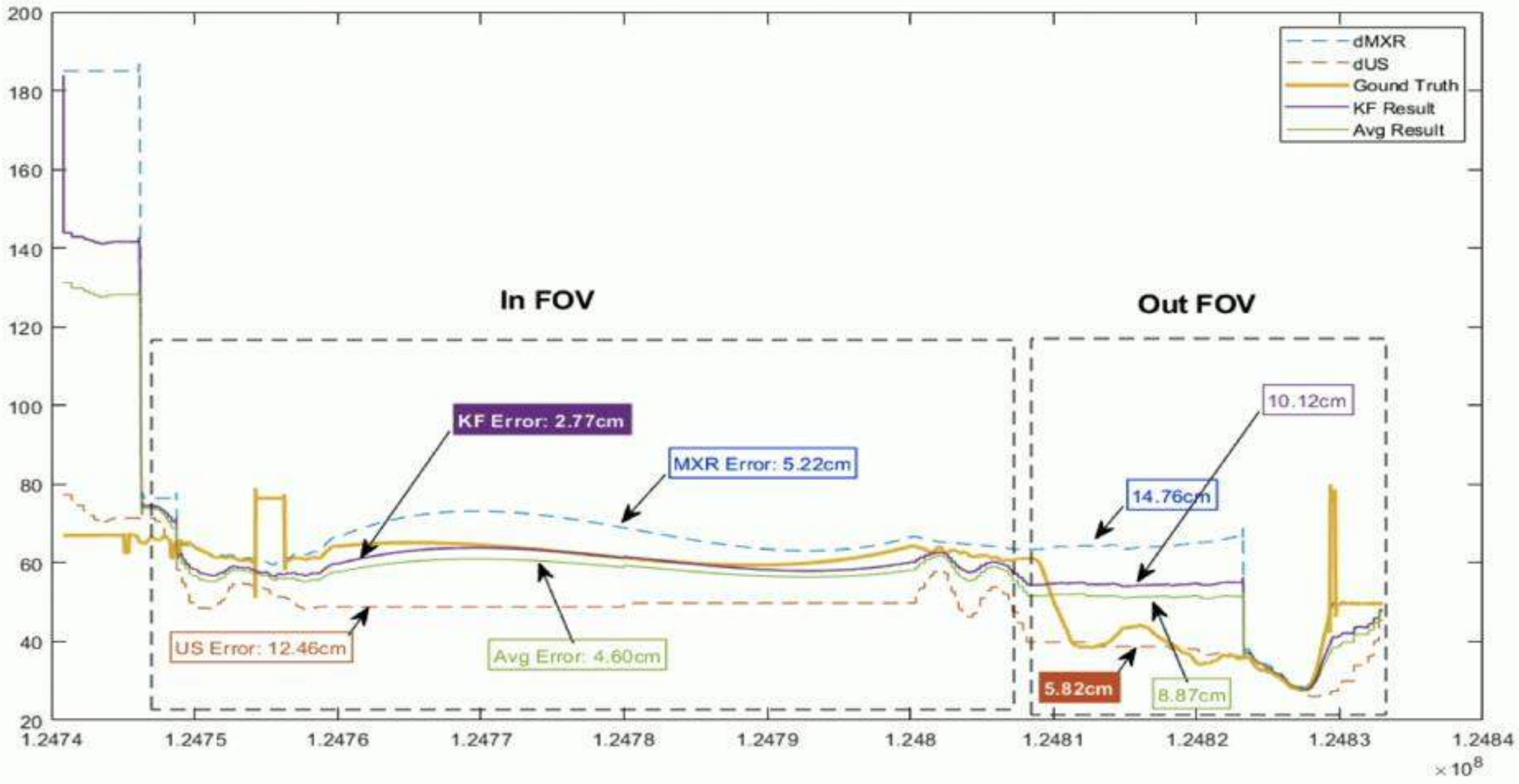
- Ultrasound distance tracking



Average Tracking Distance Error (cm)		
In FOV (Status High)	*MXR*	*3.4859+3.0068*
	US	*8.7898+6.208*
Out FOV (Status Approx)	*MXR*	*23.5274+14.2919 (depends on the movement)*
	US	*8.4739+8.1515*

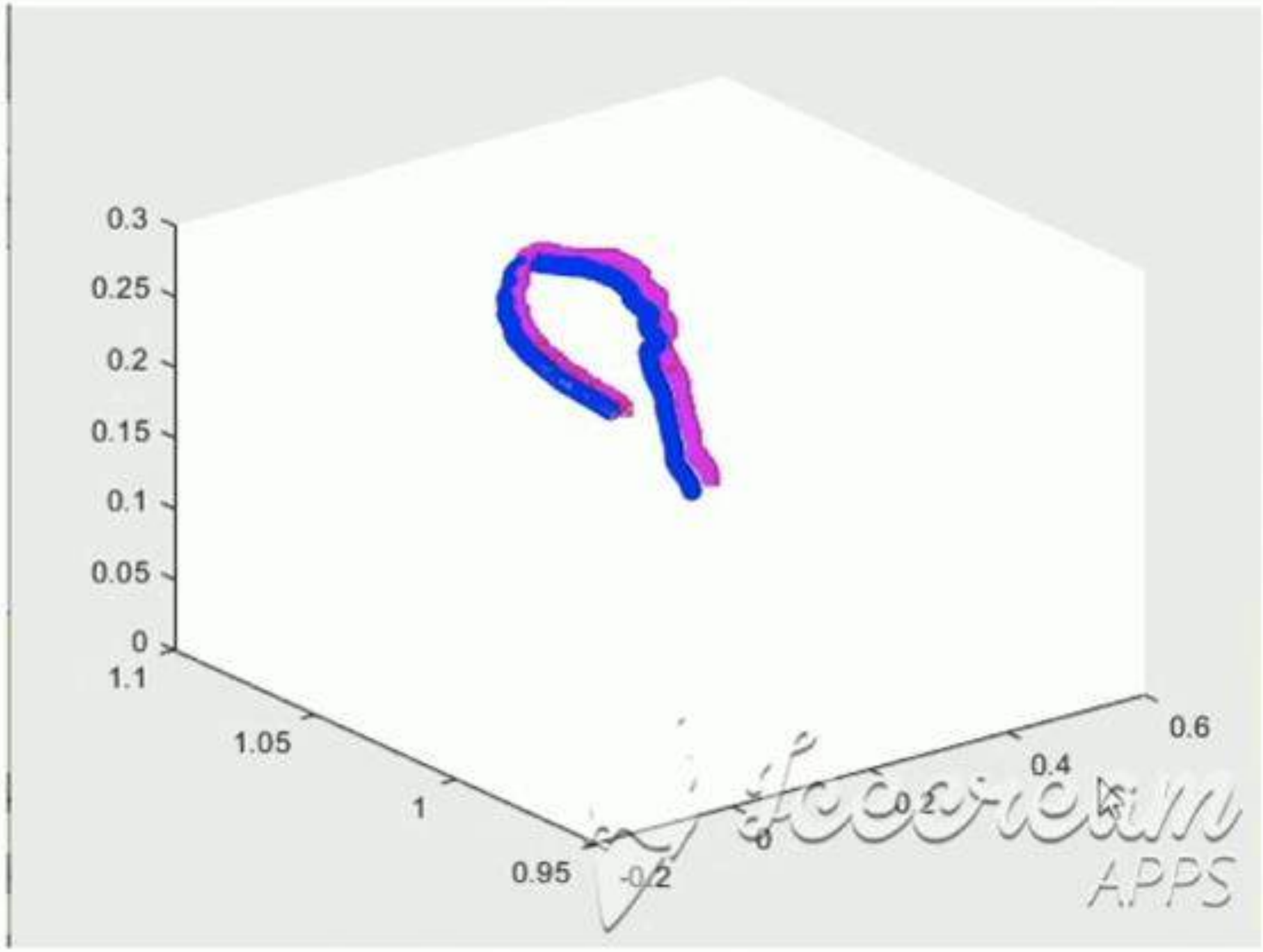
Tracking Performance

- Ultrasound distance tracking



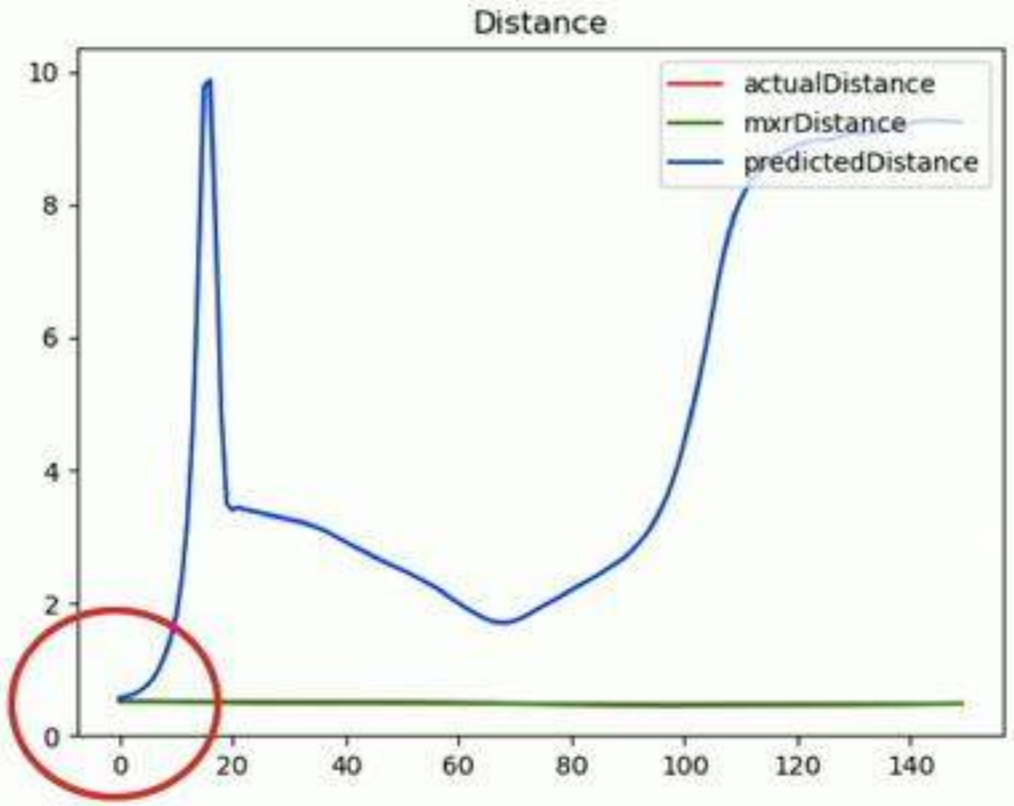
Tracking Performance

- LSTM tracking in FOV

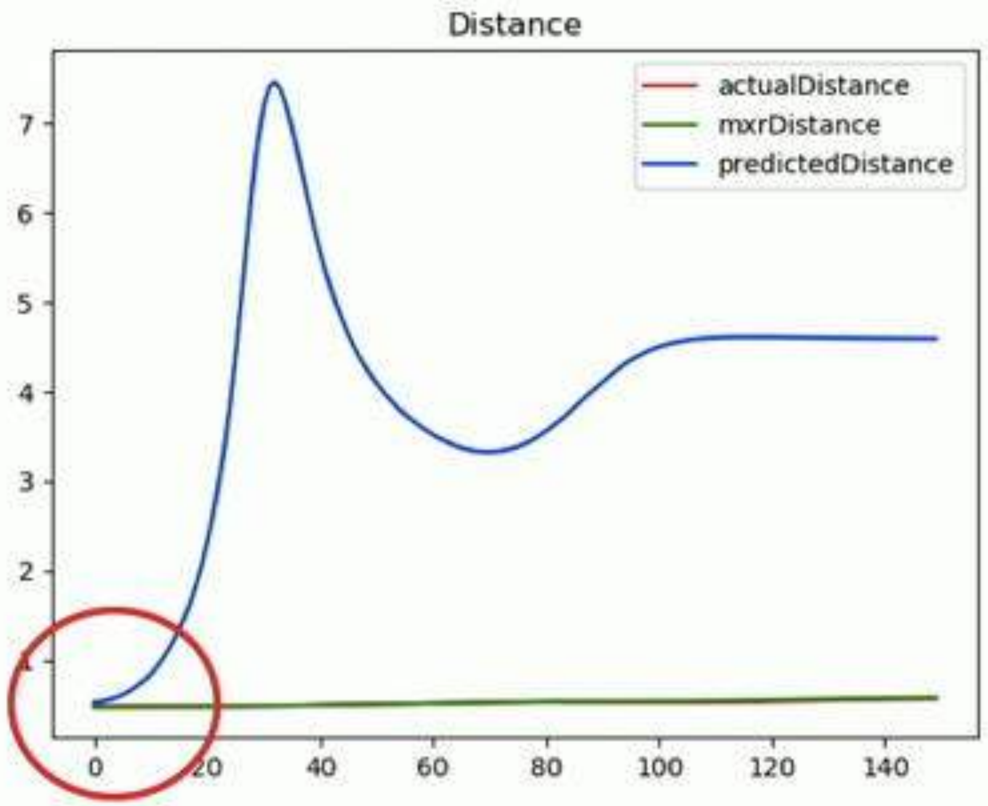


Tracking Performance – Out of FOV

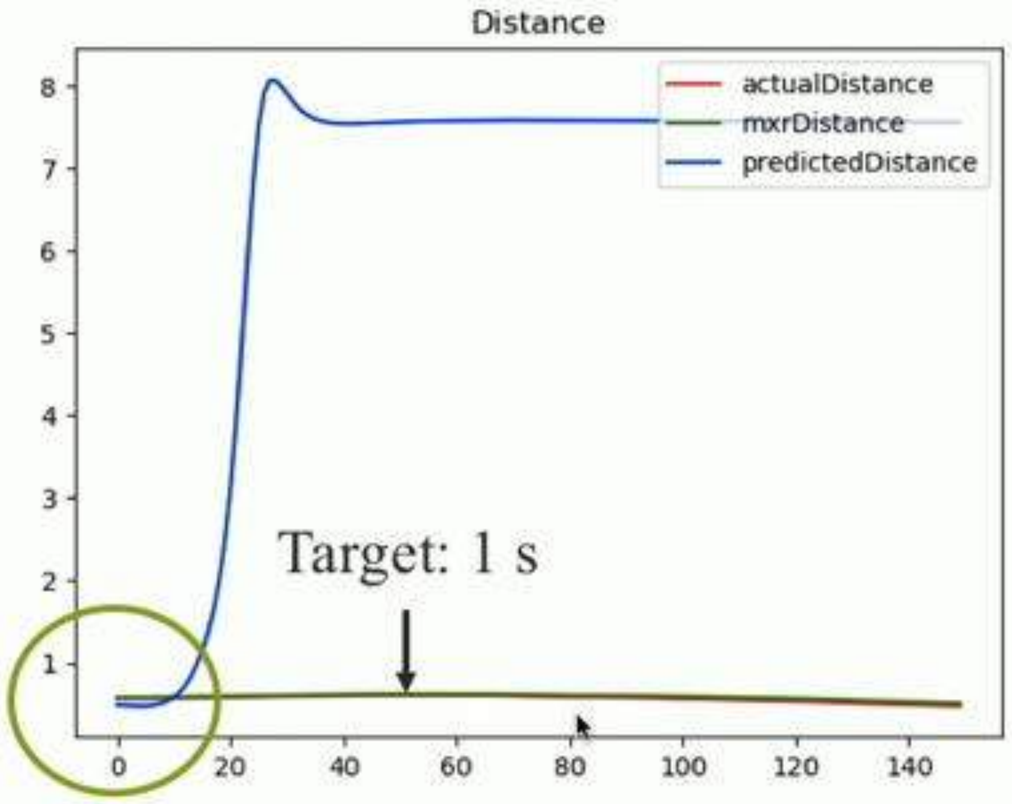
- LSTM tracking with different window size



Window Length = 51
(Using the past 1 s info)



Window Length = 101
(Using the past 2 s info)



Window Length = 201
(Using the past 4 s info)

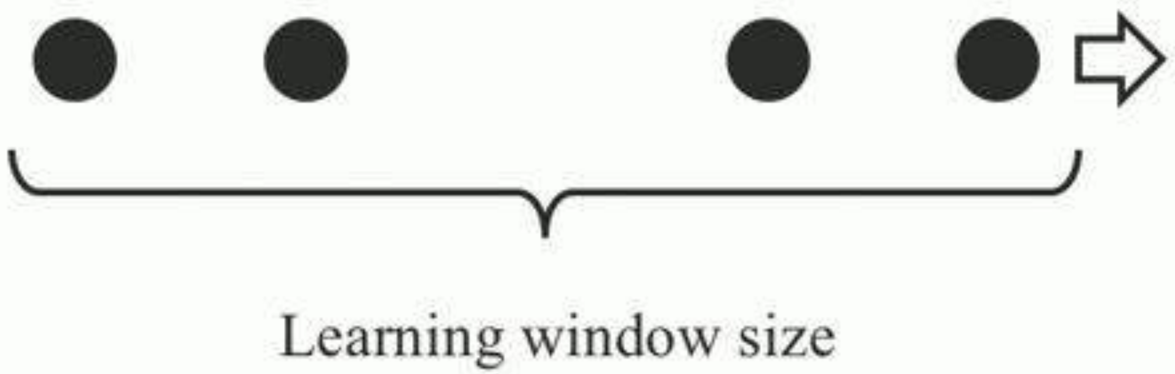
Able to predict up to 200 ms

Ongoing: Longer Out of FOV Tracking

- De-trend data, remove non-stationarity
- Larger models, hierarchical LSTMs, Windowed MLP
- Other forecasting strategies
  - Trade off computation for tracking accuracy
  - Direct H-step ahead forecasting, multiple input multiple output models

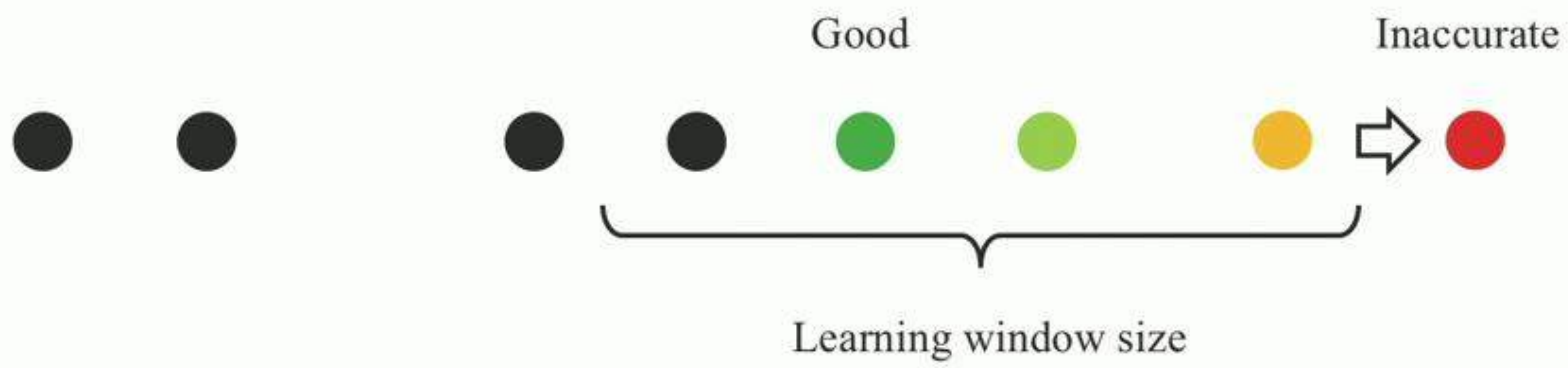
Ongoing: Longer Out of FOV Tracking

- Direct H-step ahead forecasting



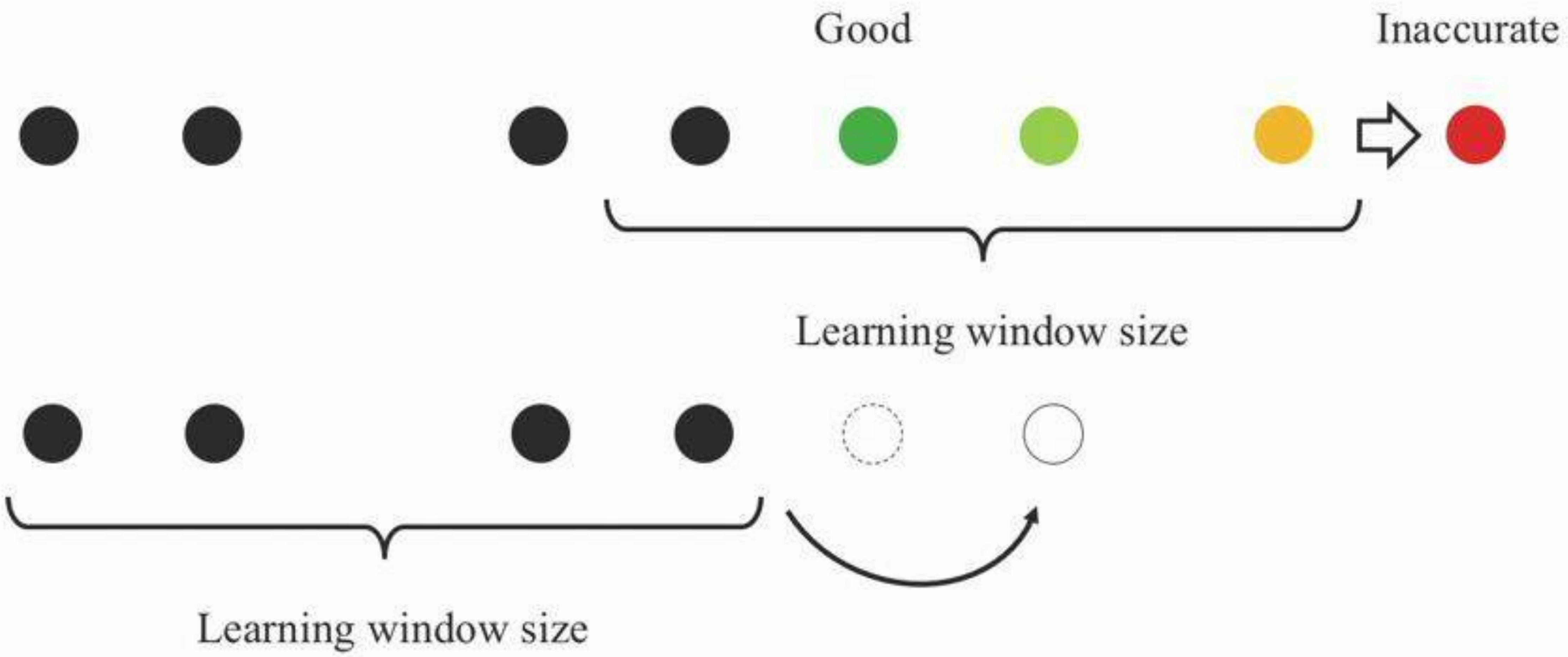
Ongoing: Longer Out of FOV Tracking

- Direct H-step ahead forecasting



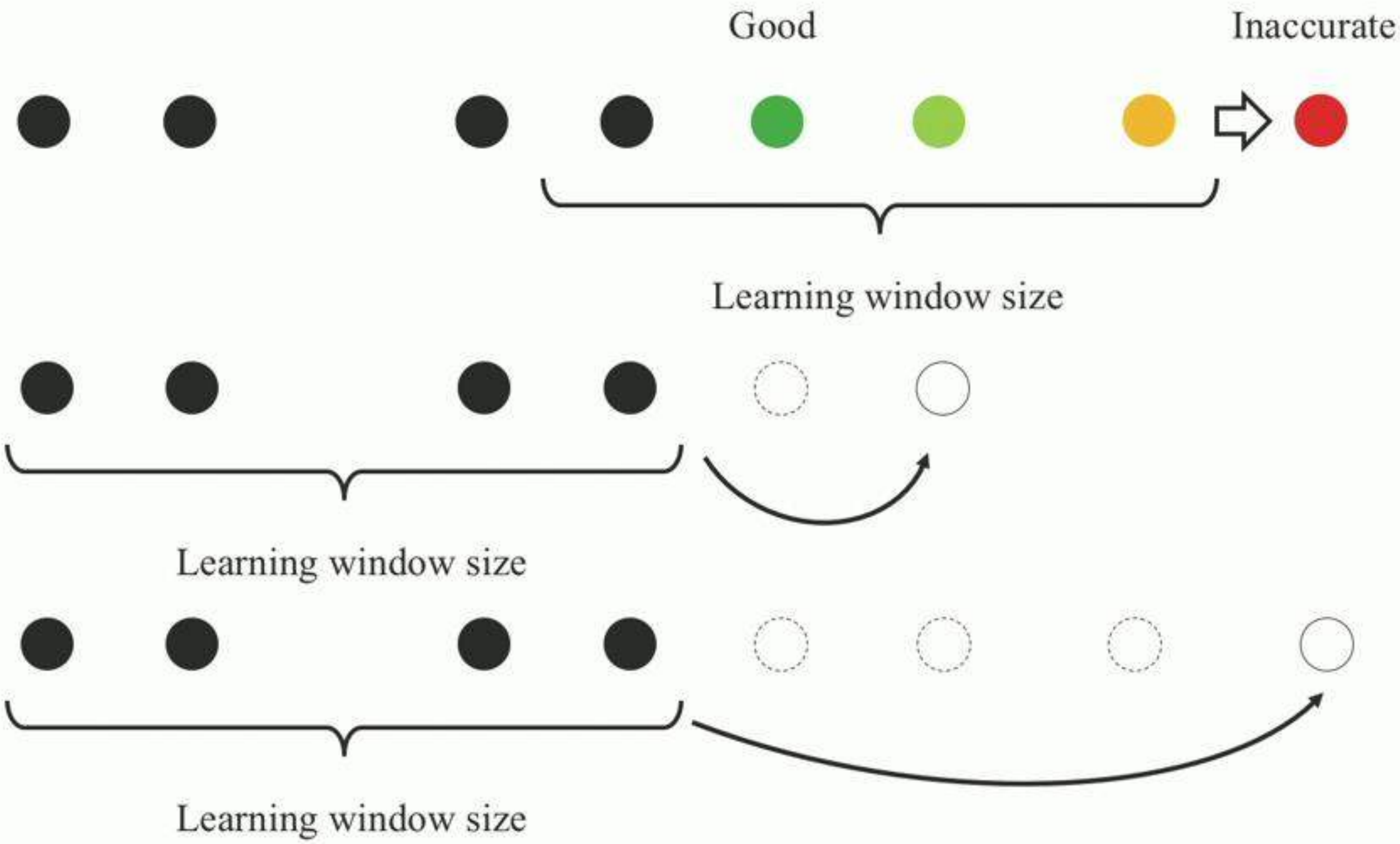
Ongoing: Longer Out of FOV Tracking

- Direct H-step ahead forecasting



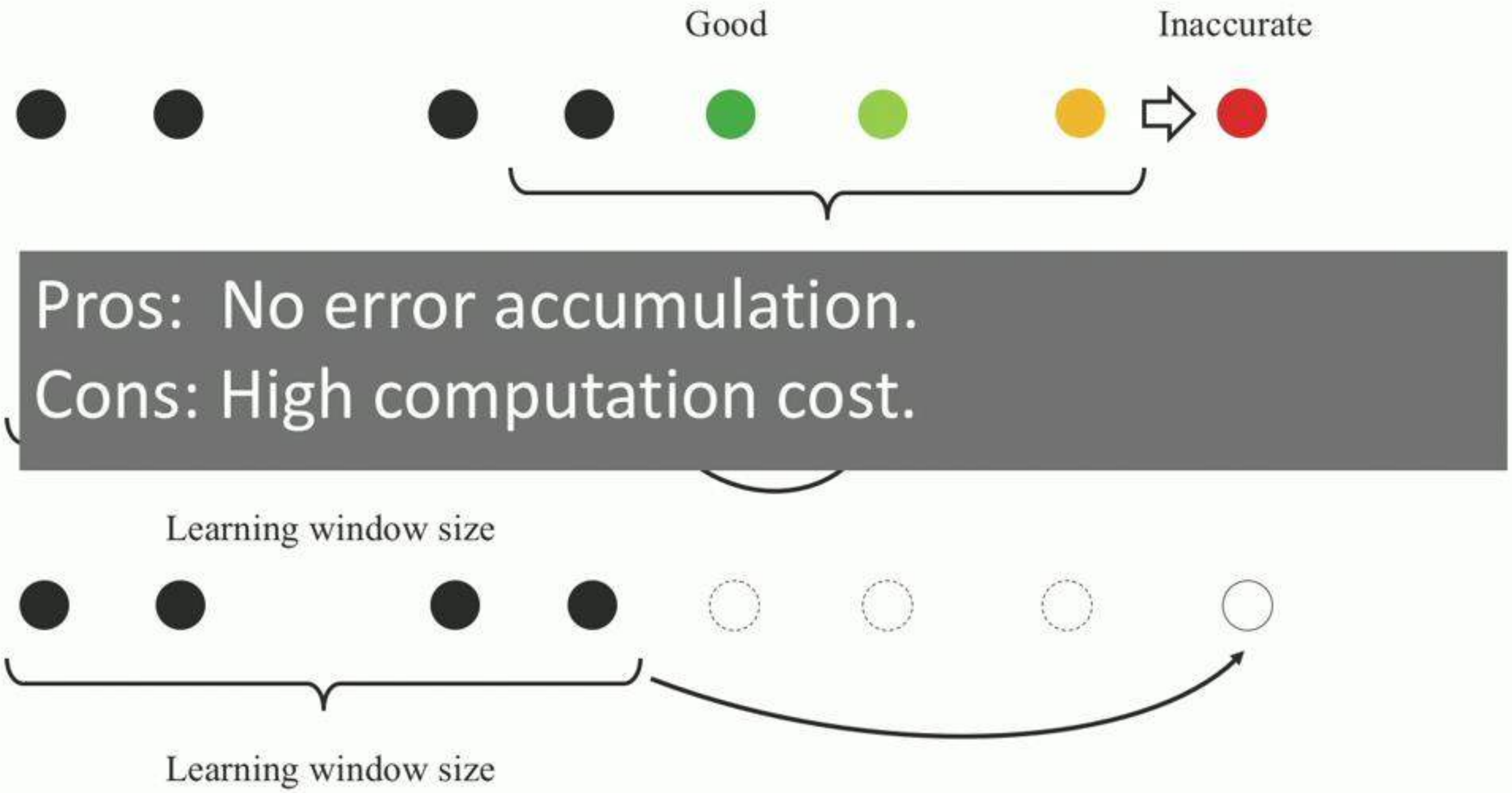
Ongoing: Longer Out of FOV Tracking

- Direct H-step ahead forecasting



Ongoing: Longer Out of FOV Tracking

- Direct H-step ahead forecasting



Ongoing: Longer Out of FOV Tracking

- Multiple input multiple output models

Ongoing: Longer Out of FOV Tracking

- Multiple input multiple output models

Pros: 1. Only one model is trained.
2. No error accumulation.

Cons: 1. Prediction length is fixed. Less flexibility.

Conclusions

- Built an ultrasound ranging system
  - Distance accuracy of around 8 cm
- Develop an iterative time series prediction model based on LSTM
  - Prediction range up to 200 ms
- Establish a sensing fusion system which fuses the available data to estimate the position information.

Acknowledgement

- My mentor Shuayb Zarar
- Audio and Acoustics Research Group
- Microsoft Research

Microsoft

Thank You