A Data-Fusion Method using Bayesian Approach to Enhance Raw Data Accuracy of Position and Distance Measurements for Connected Vehicles

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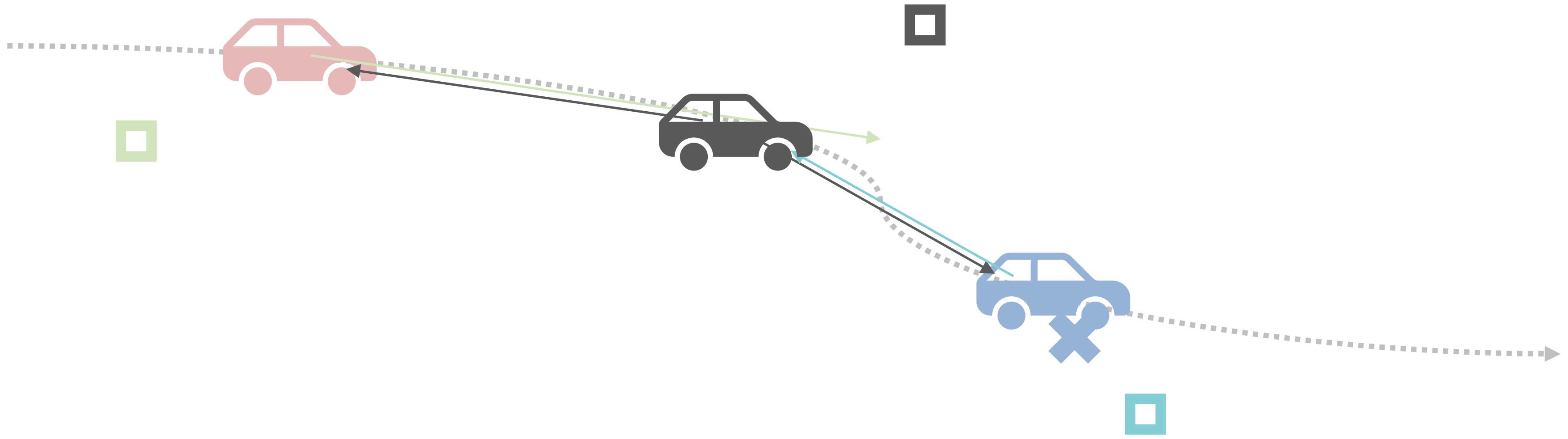
Multi-source Data in Connected Environment

- Each vehicle has three sensor measurements:
  - position of the designated vehicle,
  - distance to the preceding vehicle, and
  - distance to the following vehicle.



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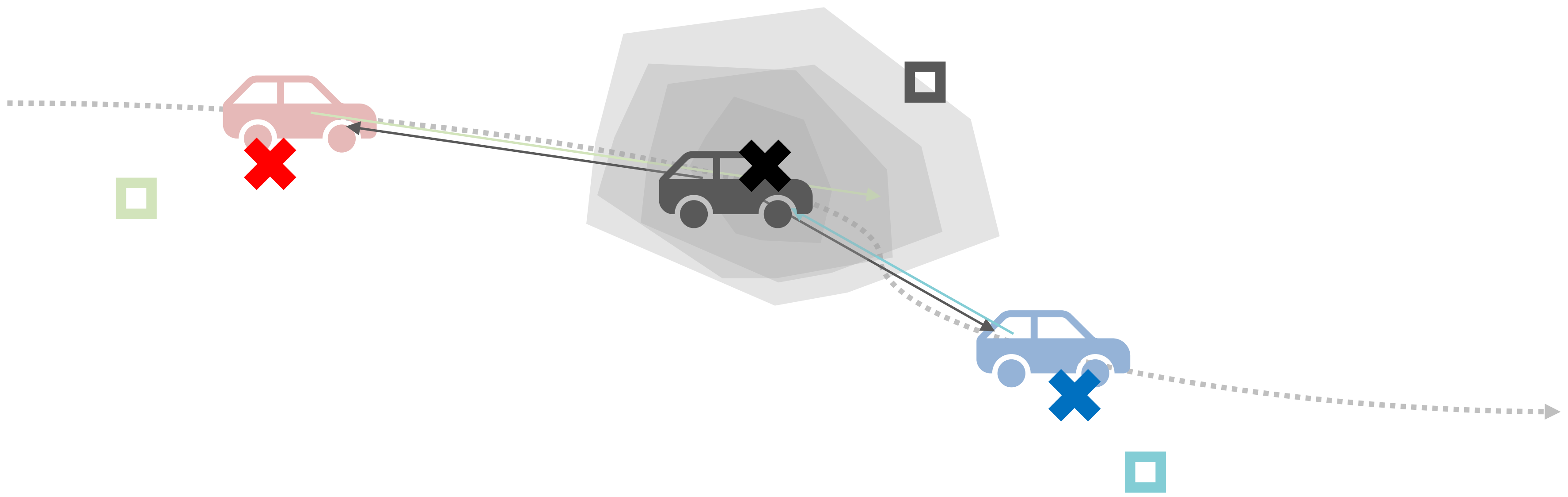
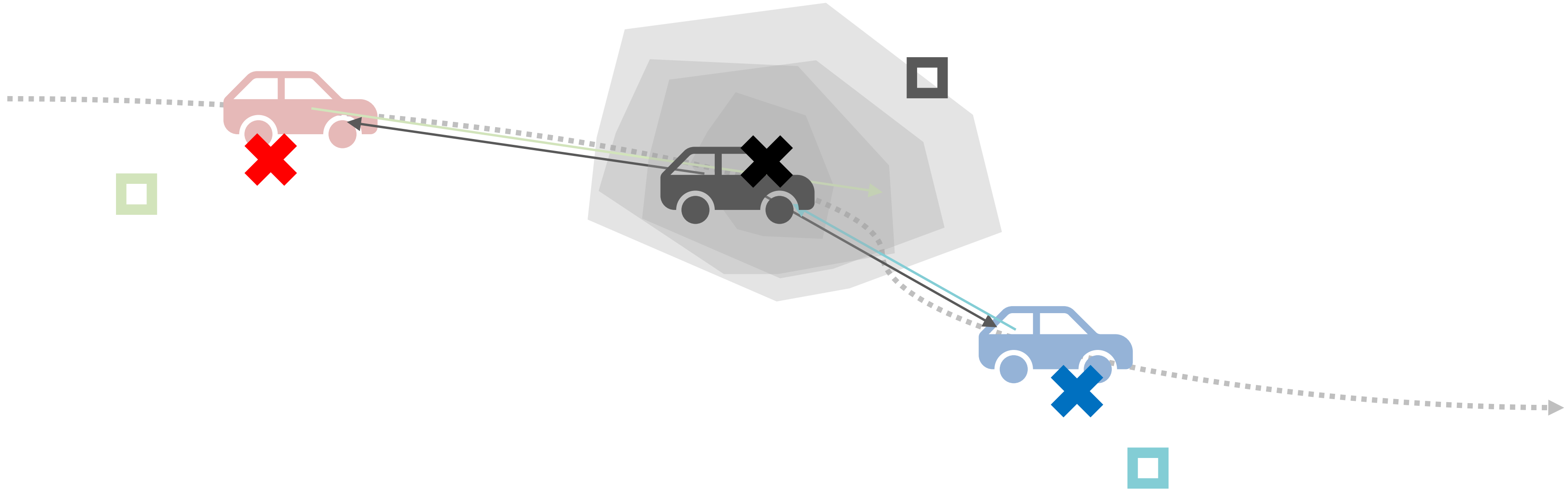
Problem to Solve

- How can we improve the accuracy of the position and distance measurements by aggregating the multi-source data?

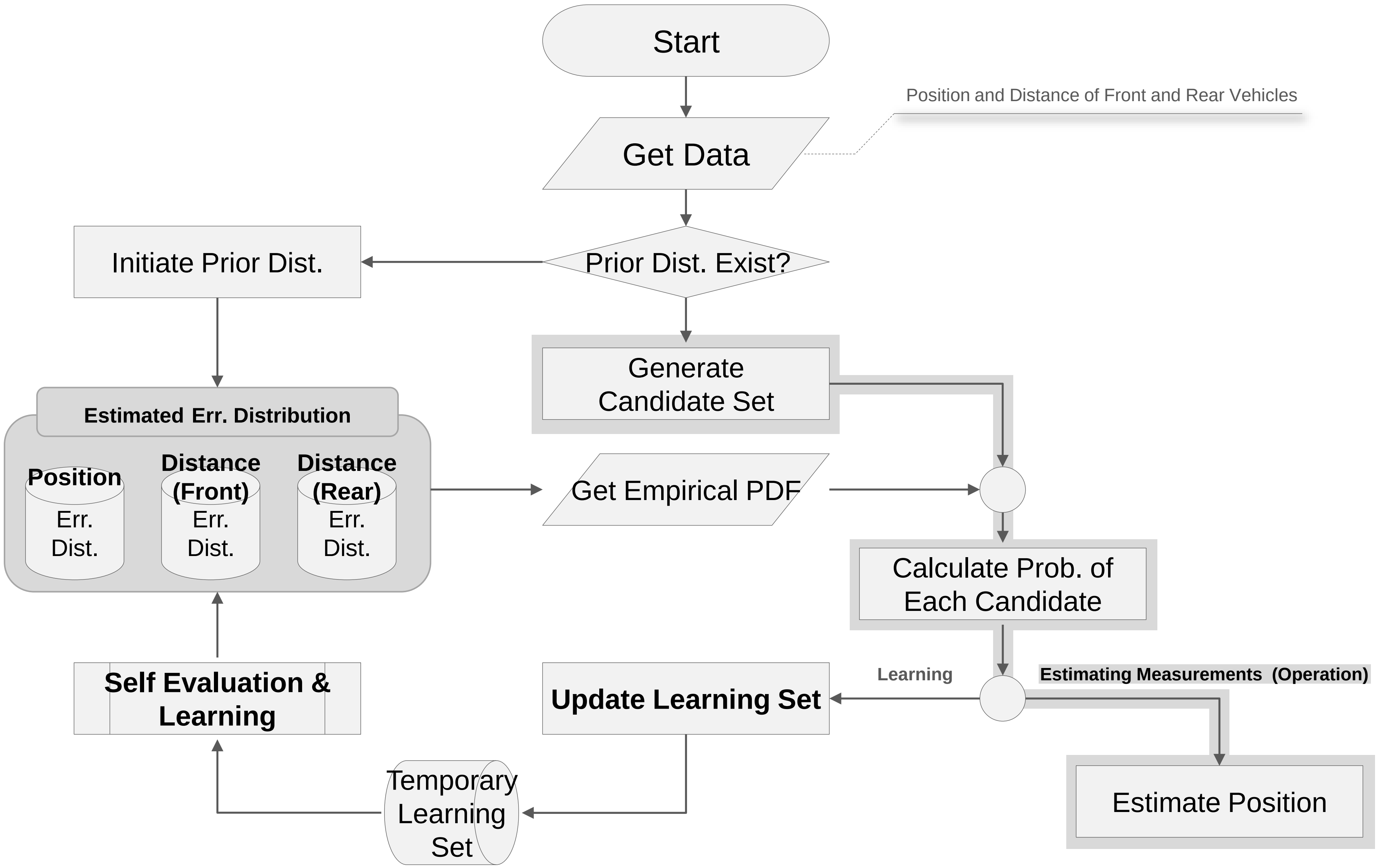


Key Ideas of Proposed Method

- Utilize the given information as much as possible.
- Estimate error distribution of each sensor measurement.
- Apply self-learning scheme that continuously update the estimated error distribution.



Flowchart of Proposed Method



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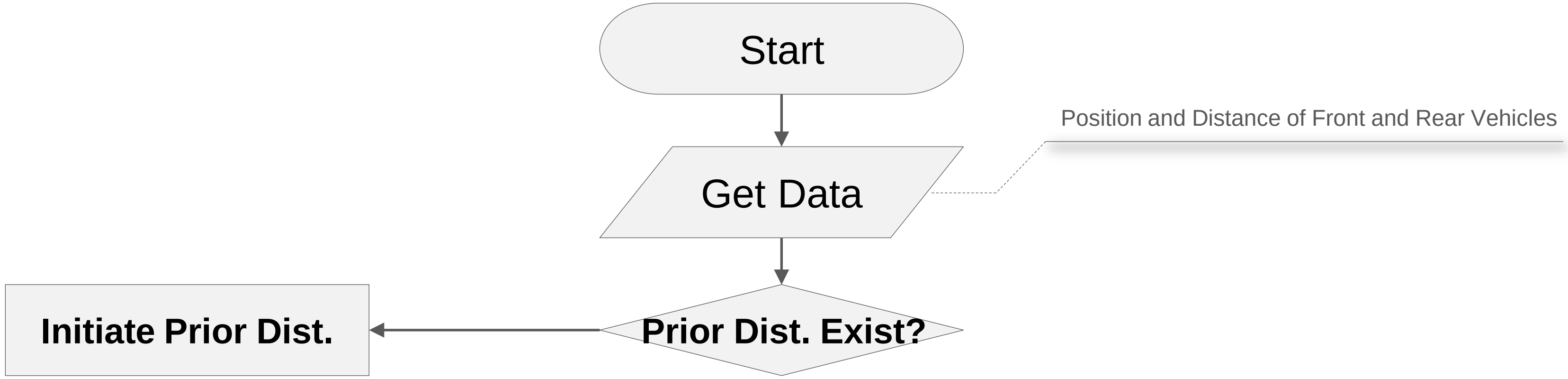
Flowchart of Proposed Method

(1) position of the designated vehicle;
(2) distance measured from the designated vehicle to the preceding vehicle;
(3) distance measured from the designated vehicle to the following vehicle;

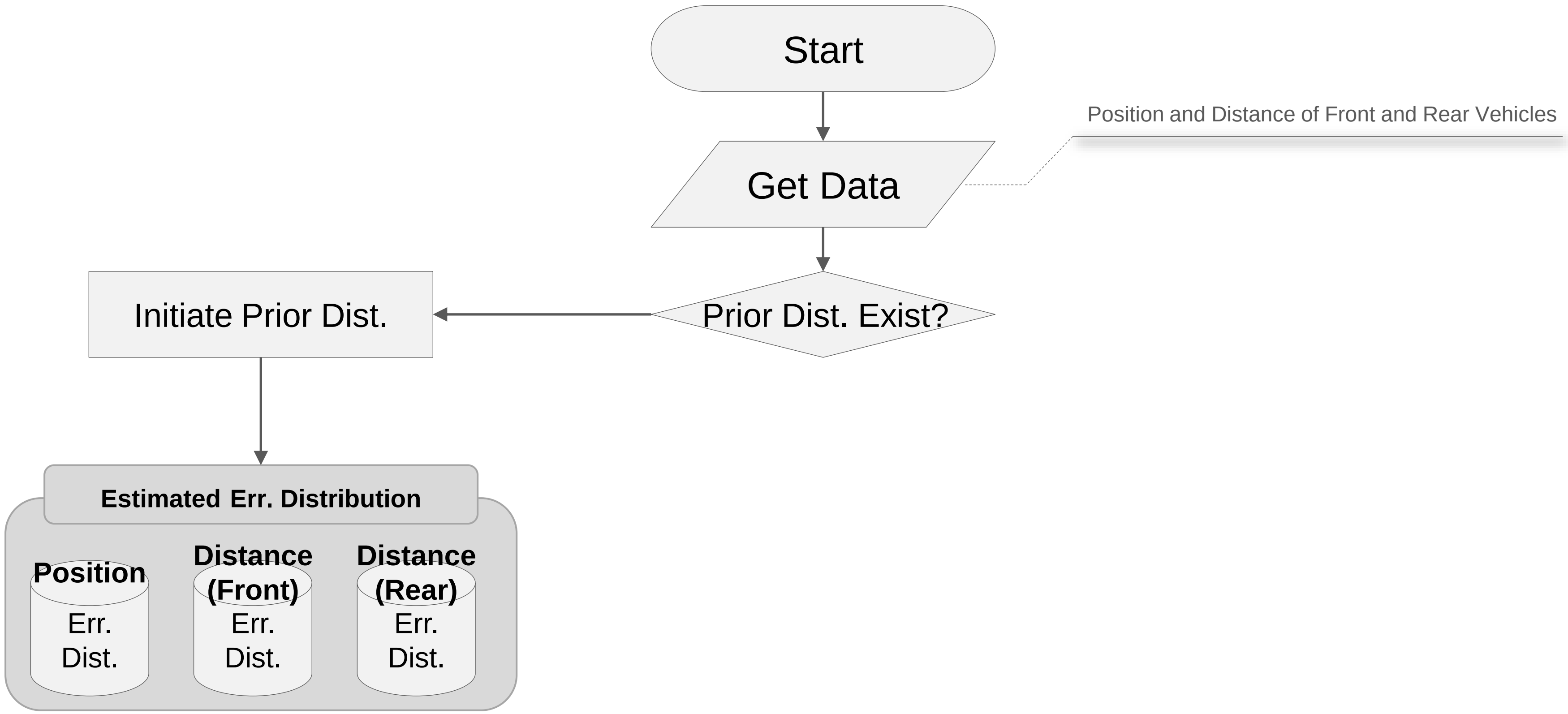
(4) position of the preceding vehicle;
(5) distance measured from the preceding vehicle to the designated vehicle;

(6) position of the following vehicle; and
(7) distance measured from the following vehicle to the designated vehicle.

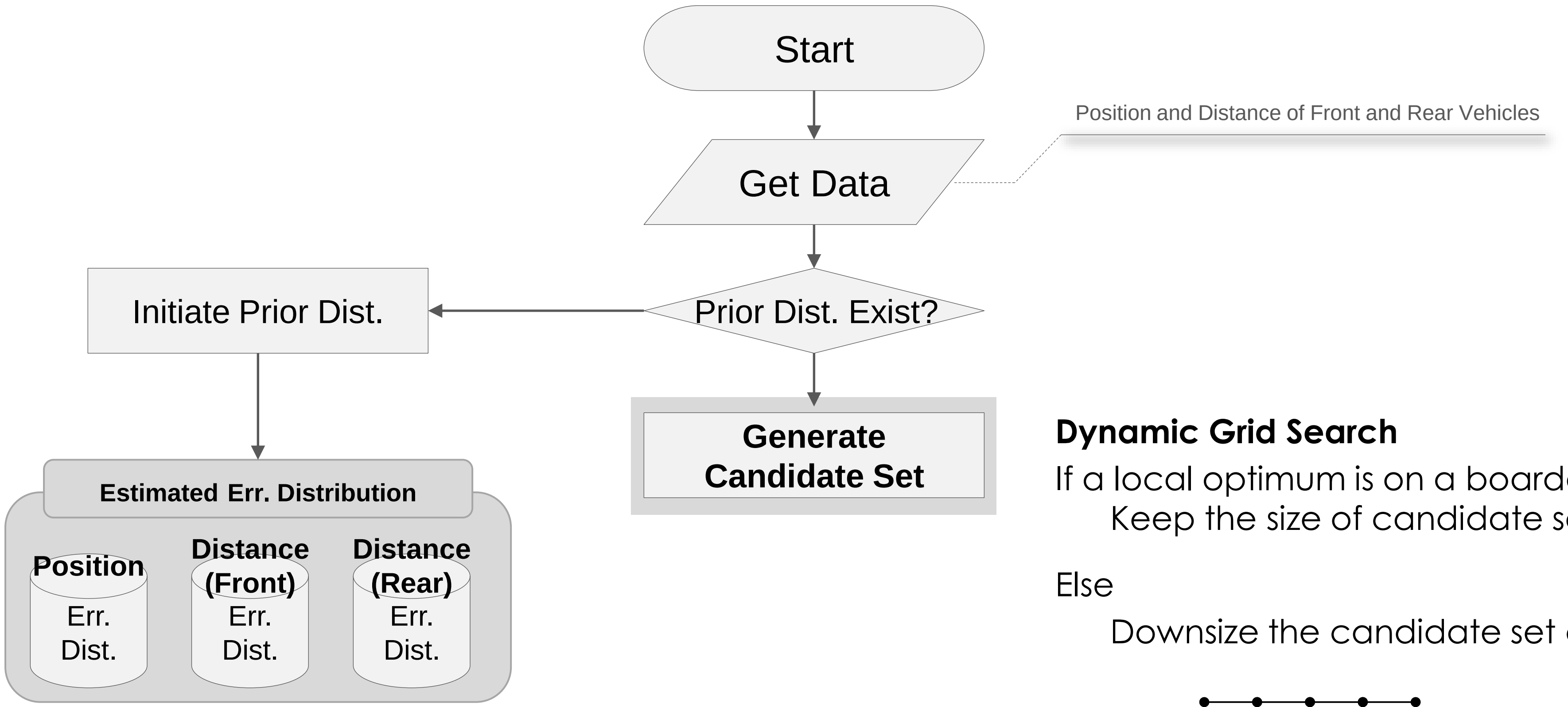
Flowchart of Proposed Method



Flowchart of Proposed Method



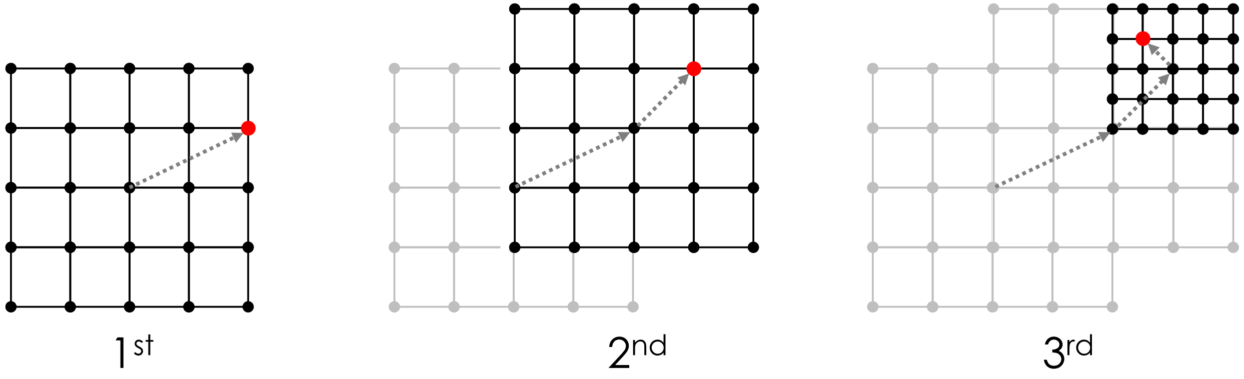
Flowchart of Proposed Method



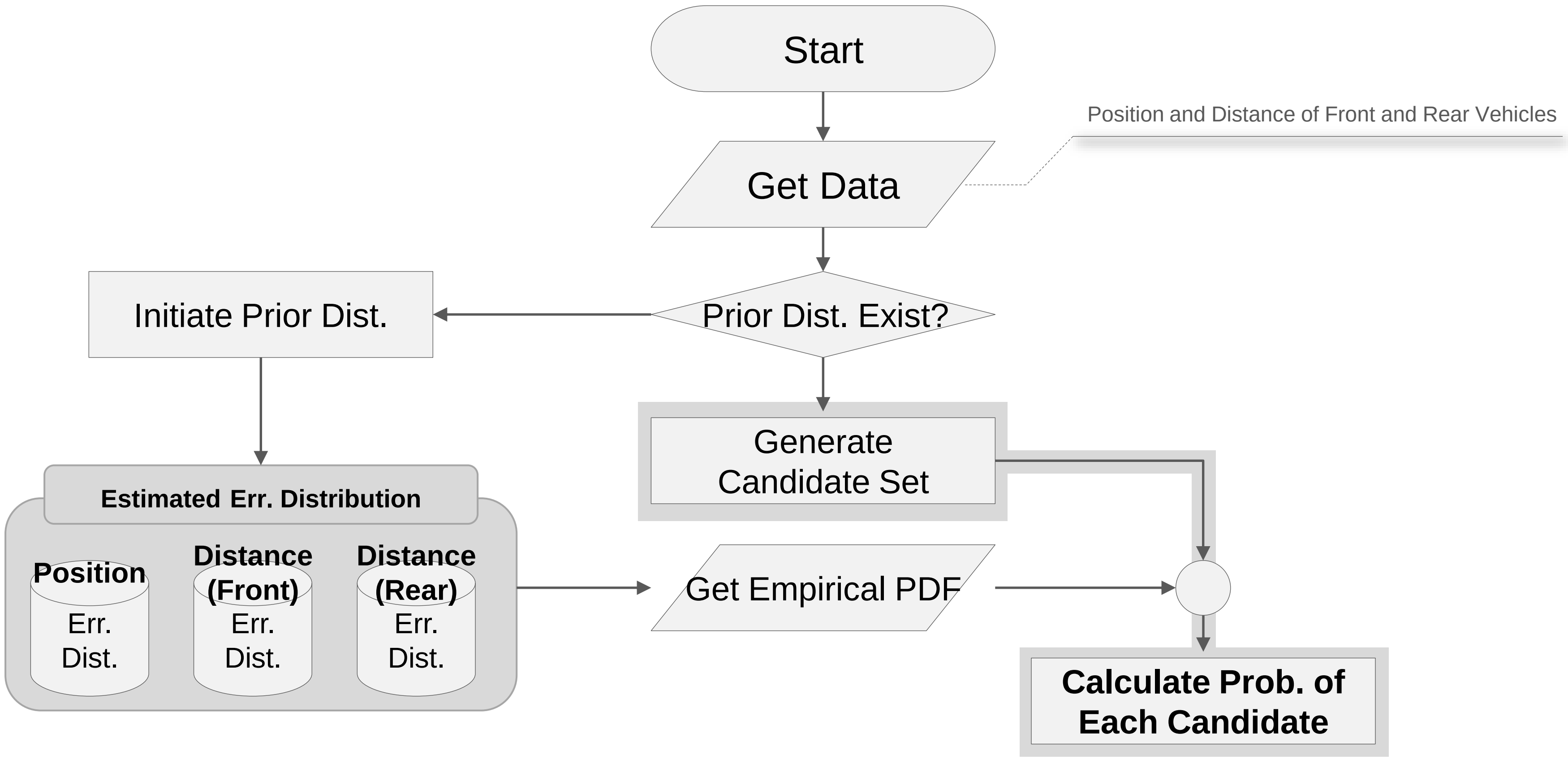
Dynamic Grid Search

If a local optimum is on a boarder,
Keep the size of candidate set area

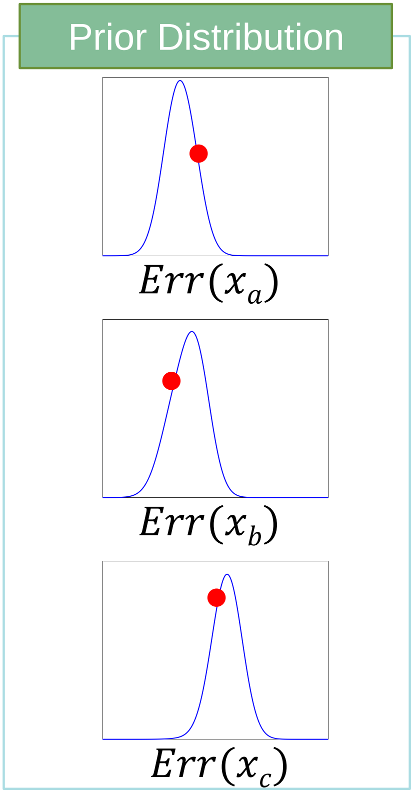
Else
Downsize the candidate set area



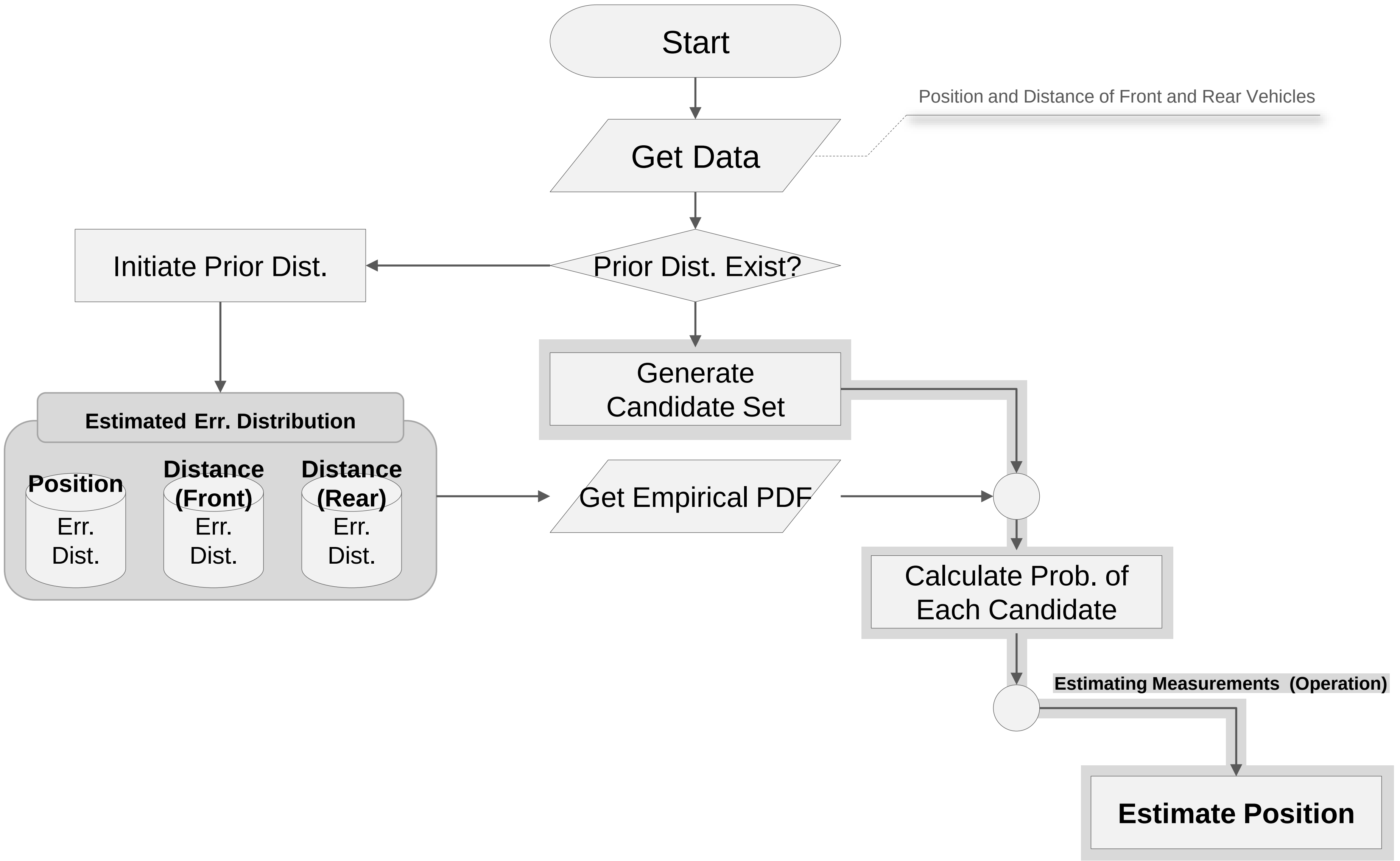
Flowchart of Proposed Method



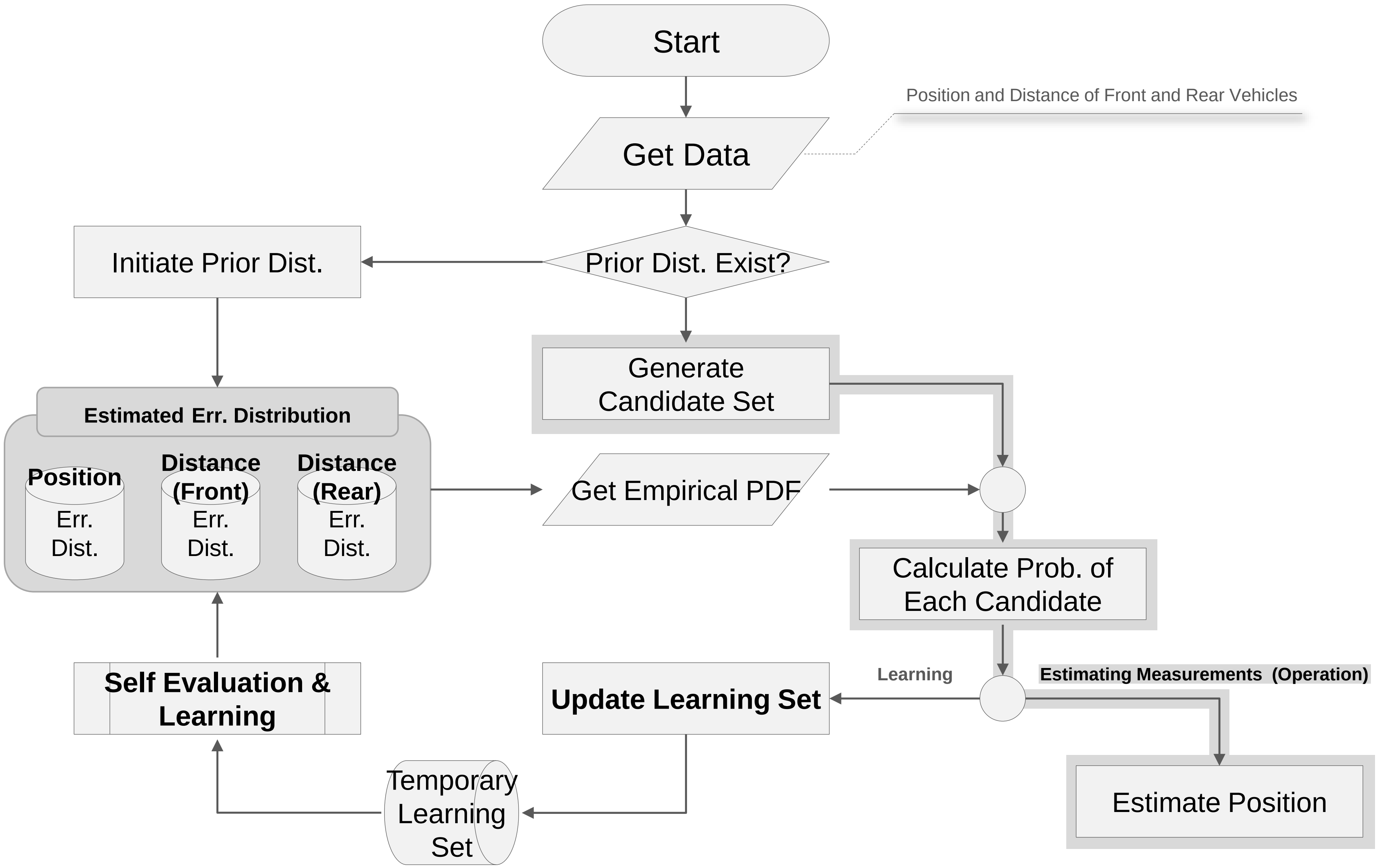
Candidate	$Err(x_a)$	$Err(x_b)$	$Err(x_c)$	Prob.
$\hat{x}_{T1}$	$x_a - \hat{x}_{T1}$	$x_b - \hat{x}_{T1}$	$x_c - \hat{x}_{T1}$	$P(\hat{x}_{T1})$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
$\boldsymbol{\hat{x}_{Tn}}$	$\boldsymbol{x_a - \hat{x}_{Tn}}$	$\boldsymbol{x_b - \hat{x}_{Tn}}$	$\boldsymbol{x_c - \hat{x}_{Tn}}$	$\boldsymbol{P(\hat{x}_{Tn})}$



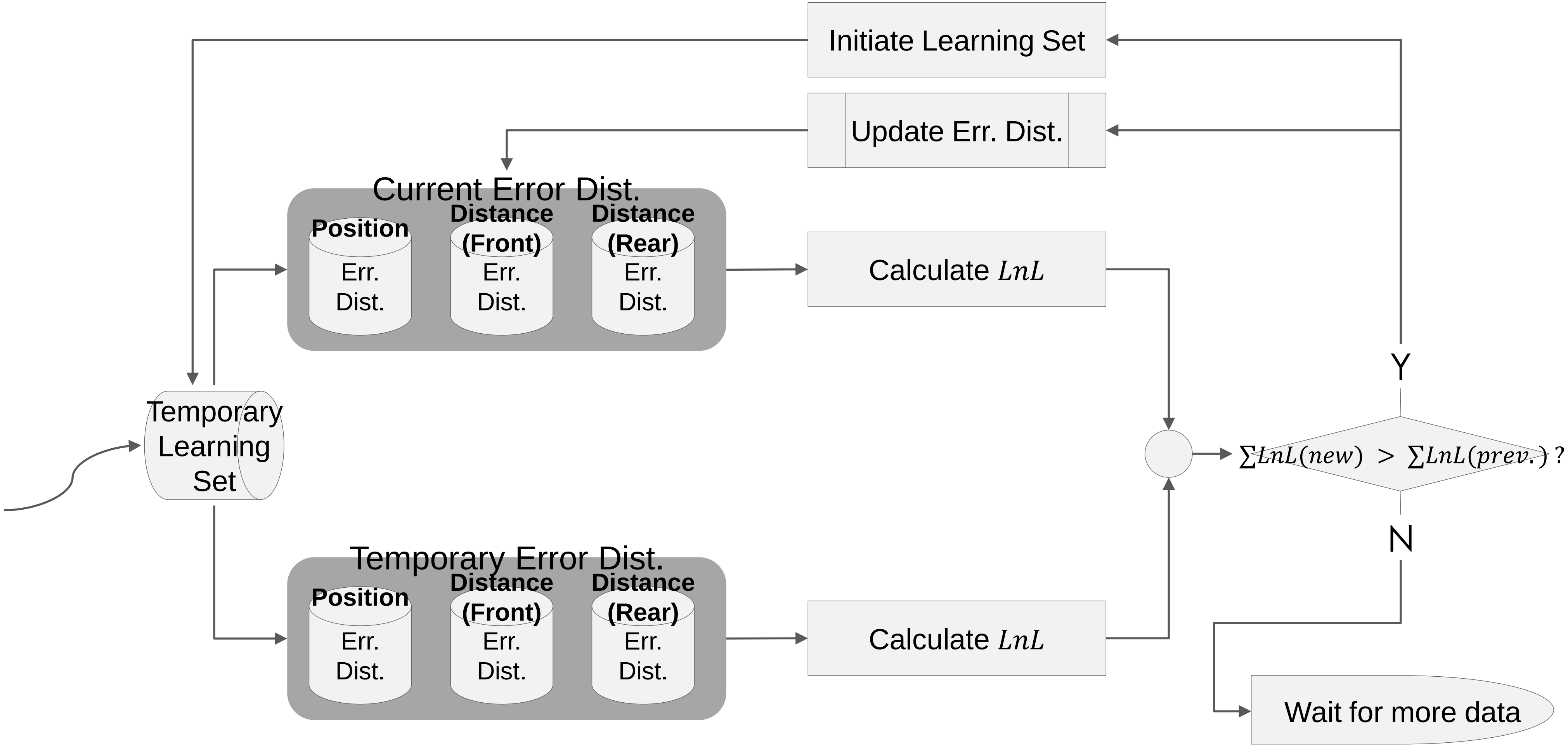
Flowchart of Proposed Method



Flowchart of Proposed Method

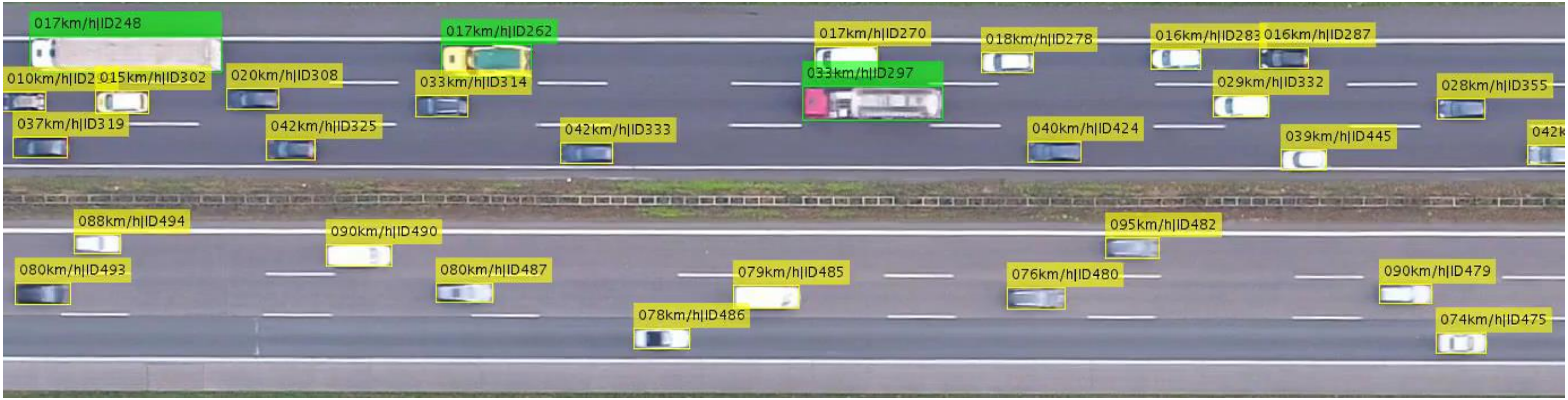


Self-Evaluation and Learning



Study Data – HighD Vehicle Trajectory

- The ‘HighD’ data is a drone-based vehicle trajectory dataset for more than 100,000 vehicles, collected from six different locations in German highways.
- To minimize the impact of specific location and time period of the data collection, the study randomly selected 30,000 frames of data as for each iteration of new training dataset.
- Still, we DO NOT have the ground truth!



Source: https://www.highd-dataset.com/

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Scenarios

- Measurement errors of sensors could vary depending on many factors, such as manufacturer, device, environment, signal interruptions, etc.
- To evaluate the impact of proposed method based on different circumstances, multiple scenarios were prepared based on the following three error ranges (in meters):
  - Bias: [-0.1 ~ +0.1], (Co)-Variance: [+0.1 ~ +0.5]
  - Bias: [-0.5 ~ +0.5], (Co)-Variance: [+0.1 ~ +1.0]
  - Bias: [-1.0 ~ +1.0], (Co)-Variance: [+0.1 ~ +3.0]
- The bias and the variance of true error distribution for each sensor were randomly selected from the uniform distribution within the above ranges.

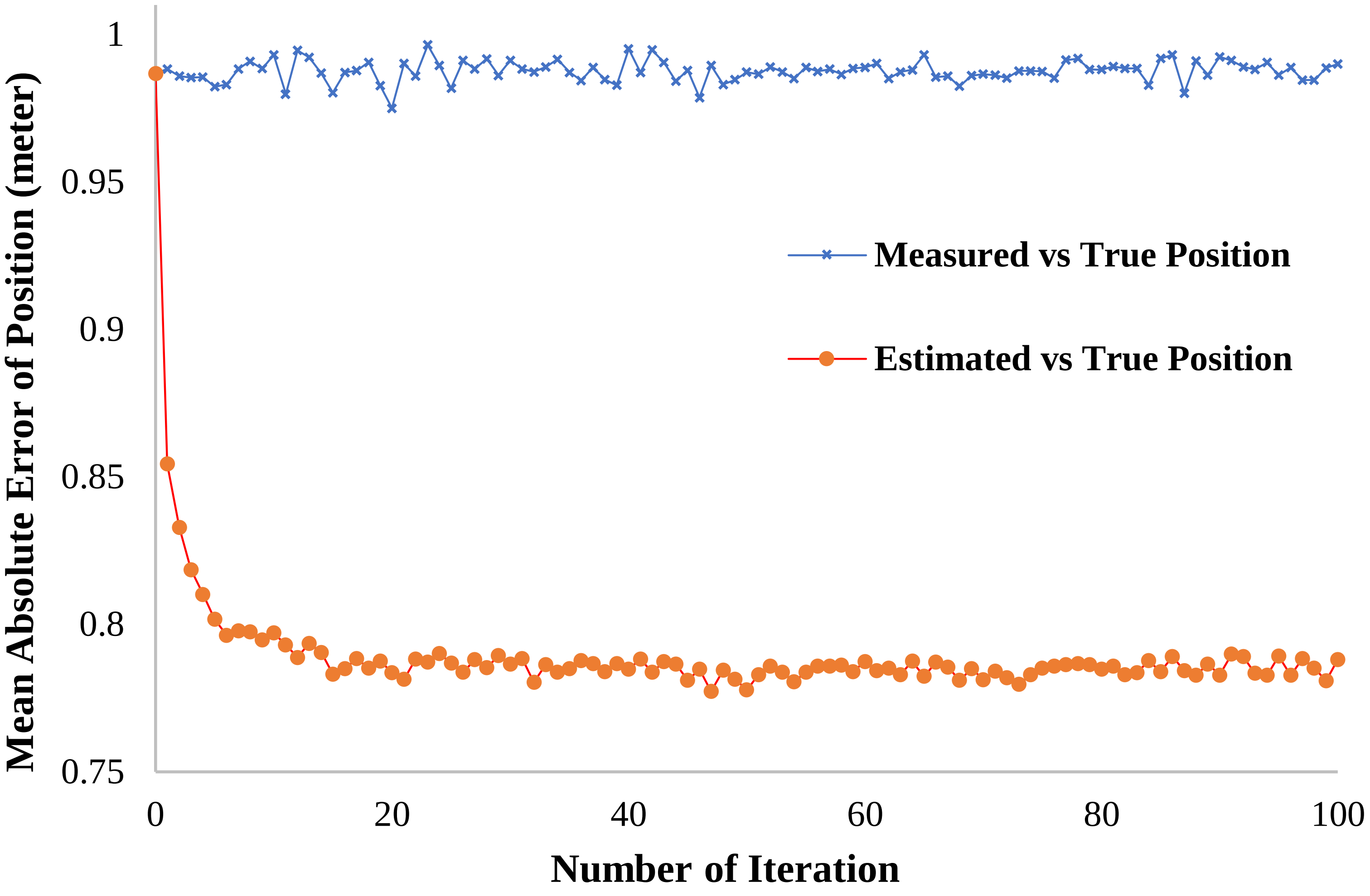
Results - Improvement of Vehicle Position Measurements

- Overall, the accuracy of position has been improved by 5 to 23%.
- Relatively, the accuracy improvement appears to be more significant when the distance measure has less bias/variance and the position measure has higher bias/variance.

Distance	**Position (X/Y coordinate)**		
	ε: [-0.1 ~ +0.1] v: [+0.1 ~ +0.5]	***ε: [-0.5 ~ +0.5] v: [+0.1 ~ +1.0]***	***ε: [-1.0 ~ +1.0] v: [+0.1 ~ +3.0]***
ε: [-0.1 ~ +0.1] v: [+0.1 ~ +0.5]	0.67 → 0.58 (- 13%)	0.98 → 0.75 (- 23%)	1.70 → 1.29 (- 24%)
ε: [-0.5 ~ +0.5] v: [+0.1 ~ +1.0]	0.68 → 0.60 (- 12%)	0.99 → 0.79 (- 20%)	1.71 → 1.34 (- 22%)
ε: [-1.0 ~ +1.0] v: [+0.1 ~ +3.0]	0.68 → 0.64 (- 5%)	0.99 → 0.87 (- 12%)	1.68 → 1.35 (- 20%)

Mean Absolute Error of Position over Number of Iterations

- In terms of the learning speed, the mean absolute error of position has decreased significantly from the first several iterations.



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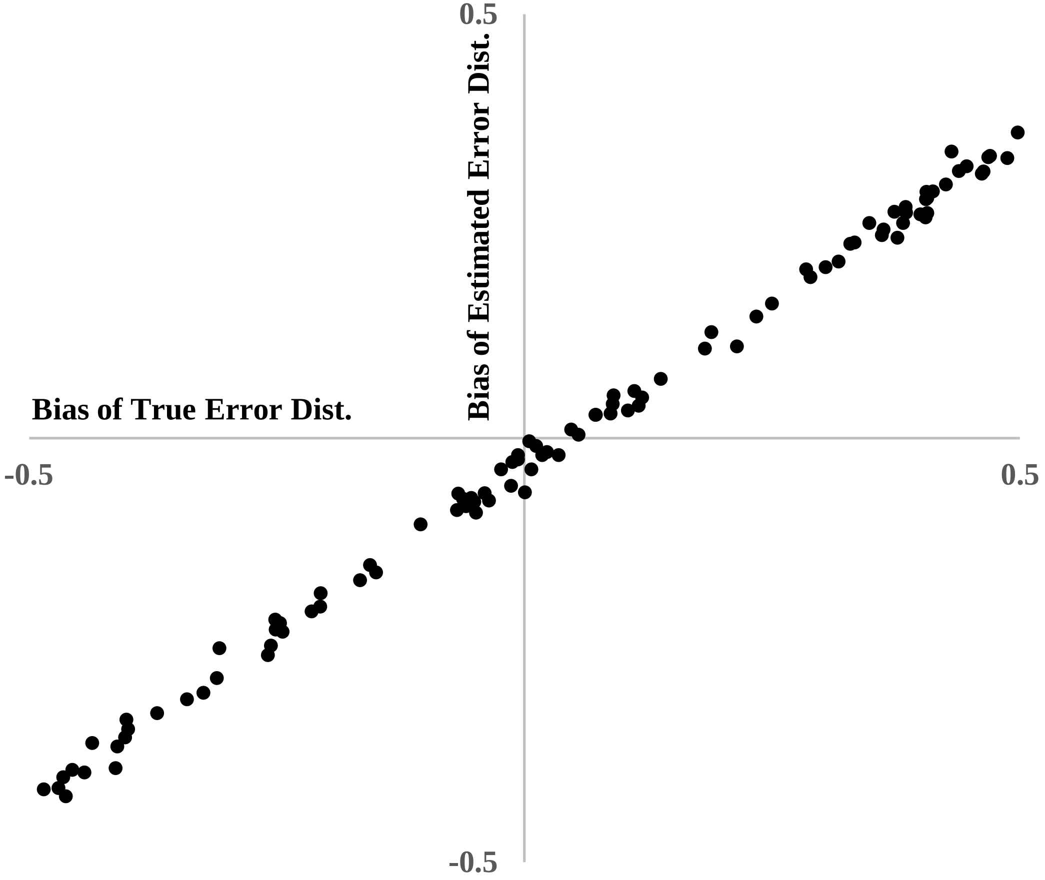
Estimated Bias of Position and Distance Errors

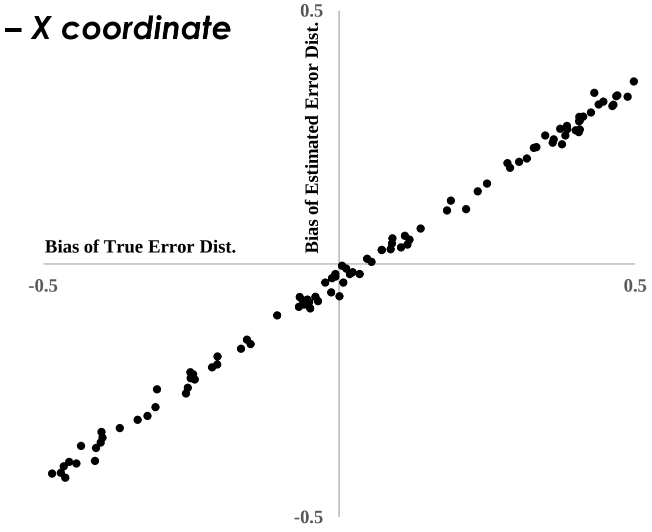
- After enough learning, the biases of x/y coordinates are very closely estimated to the true biases, with the R-squared over 0.98.



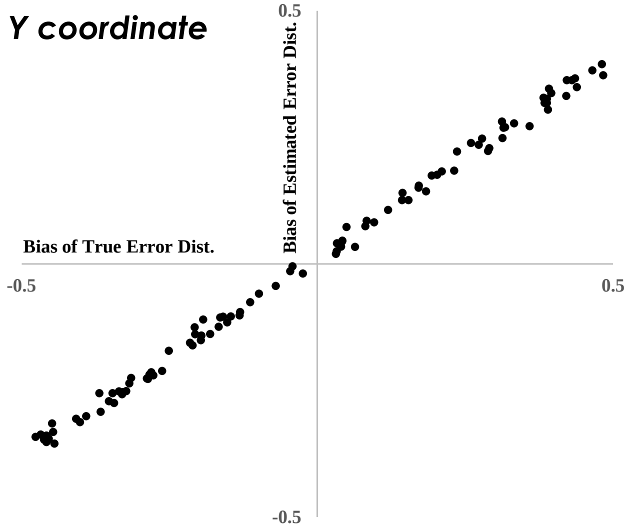
Estimated vs True Bias of Position – X coordinate

Estimated Bias of Position and Distance Errors

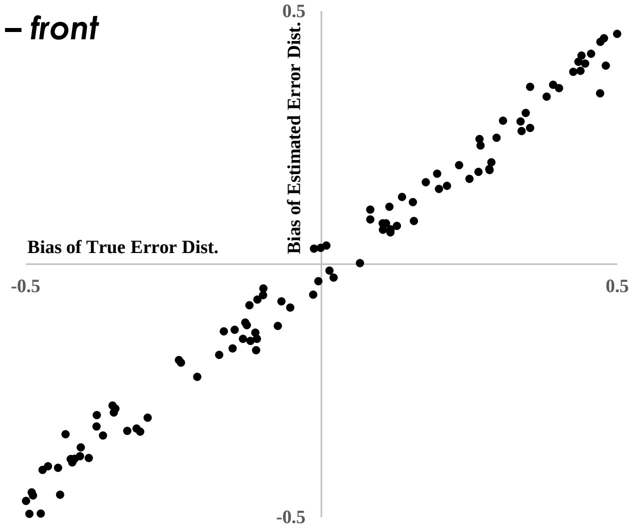
Position – X coordinate



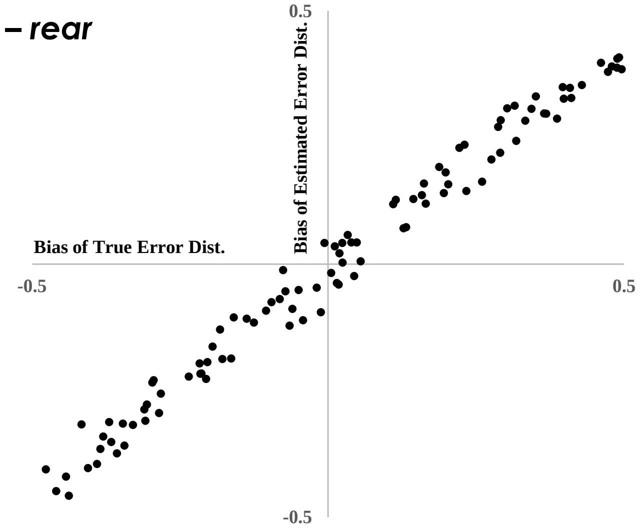
Position - Y coordinate



Distance – front



Distance – rear



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Conclusion

- The proposed model noticeably improved the accuracy of position and distance measurements.
- The key components to improve the measurement accuracy are:
  - combining the information from multiple data sources,
  - estimating the error distribution of each data source, and
  - utilizing the power of the multi-source data as more vehicles are connected.
- Potentially, the process can be applied to update the estimated error distribution where the error distribution of sensor measurement may be changed over time.
- Two critical limitations of the proposed method:
  - It is not able to estimate the exact true values of measurements even if the learning time goes infinite.
  - It assumes that overall error distributions of all sensors tend to be unbiased.

Thank you so much!

Questions?

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