Mecanismo Eficiente de Localização Cooperativa para Veículos Autônomos Conectados

Aluno: Wellington V. Lobato Junior
Orientador: Prof. Dr. Leandro A. Villas (UNICAMP)
Coorientador: Prof. Dr. Denis L. Rosário (UFPA)

UNICAMP

Agenda

Introdução

Visão Geral

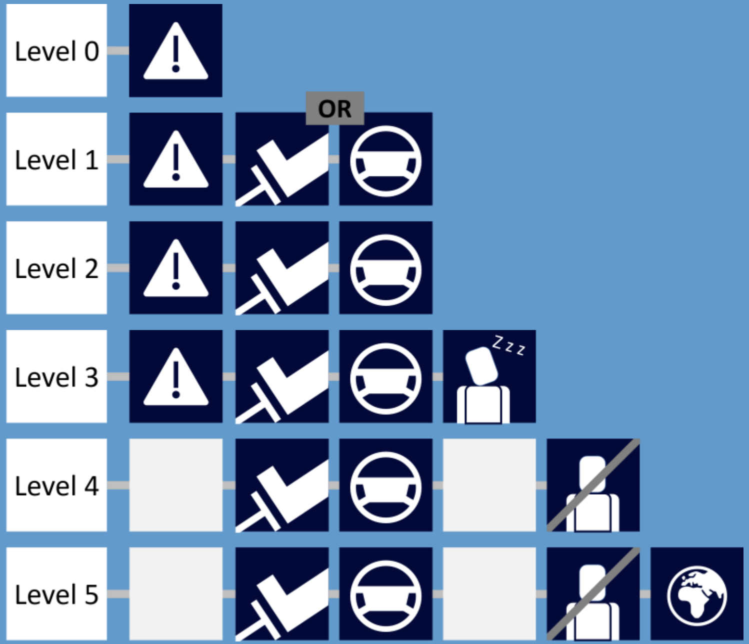
- Veículos Autônomos Conectados (Connected Autonomous Vehicle - CAV)
- Níveis de Direção Autônoma SAE(Sociedade dos Engenheiros Automotivos).
- O funcionamento dos CAVs considera três camadas: Sensoriamento, Percepção e Decisão.

Motivação

- Dados dos sensores apresentam limitações, tais como: Insegurança, Inviabilidade e Ineficiência.
- Sensores, como GPS, apresentam falhas.
- Integração de dados provenientes de várias fontes.

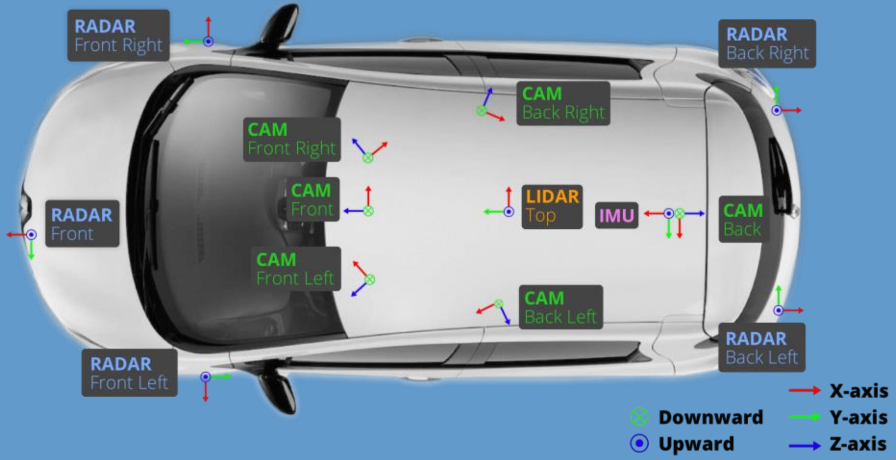
UNICAMP

Níveis de Automação SAE (Society of Automotive Engineers)



Componentes Fundamentais

- Câmeras
- LIDAR
- RADAR
- GPS
- Sensores ultrassónicos
- Algoritmos de Aprendizado de Máquina
- Comunicação (DSRC, LTE, etc.)



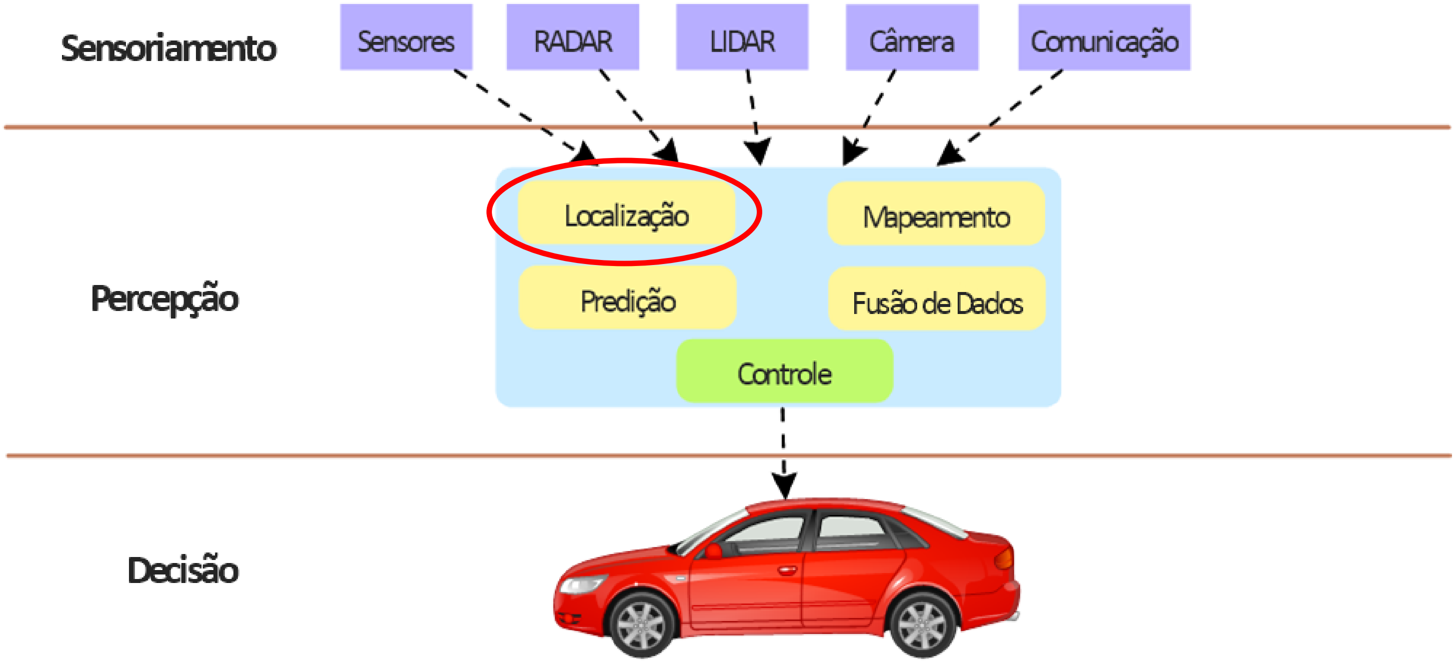


Figura 1: Arquitetura Funcional de um CAV

Pergunta de Pesquisa

- Como garantir os requisitos de localização das aplicações dos CAVs?

Application	Communication Type Rate (Hz)	Update	End-To-End Latency (ms)	Data Rate (kb/s)	Positioning (cm)
Emergency electronic brake lights	Periodic broadcast	1–10	100	1–10	-
Pre-crash sensing		10	20	20–25,000	<50–100
Pre-collision brake assist		50	50	20–25,000	30
Emergency vehicle warning		10	100	≥10	-
Overtaking vehicle warning		2–10	100	10–5000	30
Lane change assistance		2–10	100	10–5000	30
Cooperative glare reduction		2	100	≥10	-
Merging traffic turn collision risk warning		2–10	100	10–5000	-
Cooperative collision warning		10	100	≥10	30
Cooperative navigation		1–10	100	10–2000	<100
Adaptive cruise control		1–10	100	10–2000	<100
Highway platooning		≥2	≤10	≥10	30
Emergency or slow vehicle warning	Event-driven	10	100	≥10	-
Wrong way driving warning		≥1 & ≤10	100	1–10	<100
Stationary vehicle warning		≥1 & ≤10	100	1–10	<500
Traffic condition warning		1–10	100	1–10	<500
Intersection warning		10	100	10	<100
Post-crash warning		10	100	≥10	<100
Cooperative adaptive cruise control		1–10	100–300	10–2000	30

Masini, B. M., Bazzi, A., & Zanella, A. (2018). ***A survey on the roadmap to mandate on board connectivity and enable V2V-based vehicular sensor networks.*** Sensors, 18(7), 2207.

UNICAMP

Modelagem do GPS

$$X_{GPS} = X + \eta \qquad \eta \sim N(\lambda, \sigma^2)$$

$$Y_{GPS} = Y + \eta \qquad \eta \sim N(\lambda, \sigma^2)$$

Elmquist, A., & Negrut, D. (2020). ***Methods and models for simulating autonomous vehicle sensors.*** IEEE Transactions on Intelligent Vehicles, 5(4), 684-692.

UNICAMP

Tipo de Erro	Variação do Erro
Relógios de Satélite	± 2 m
Erro de Orbita	± 2.5 m
Atraso Ionosférico	± 5 m
Atraso Troposférico	± 0.5 m
Ruído do Receptor	± 0.3 m
Multipercurso	± 1 m

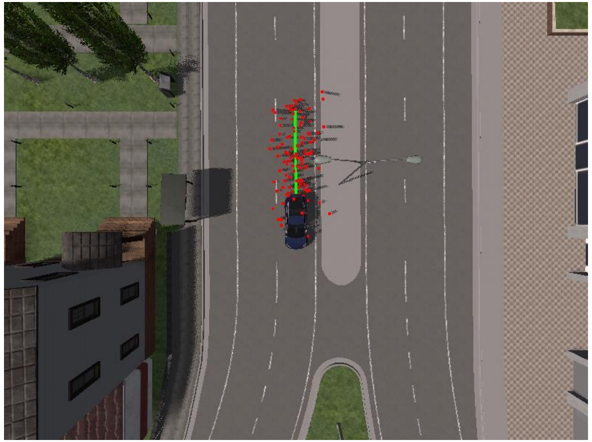


Figura 2: Erro de 1 metro

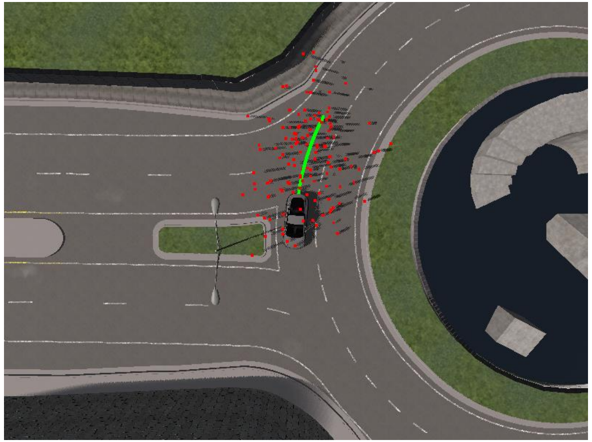


Figura 3: Erro de 2~5 metros

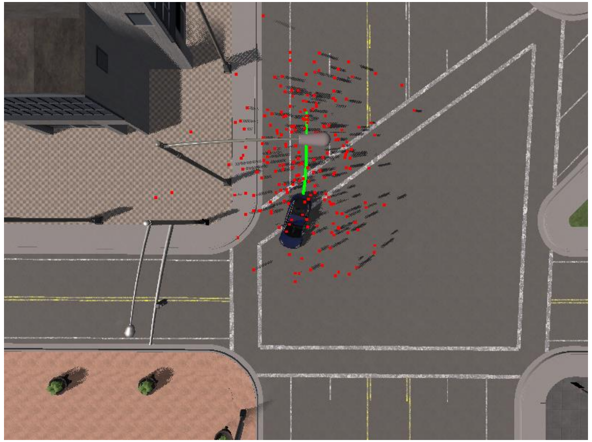


Figura 4: Erro de 5~10 metros

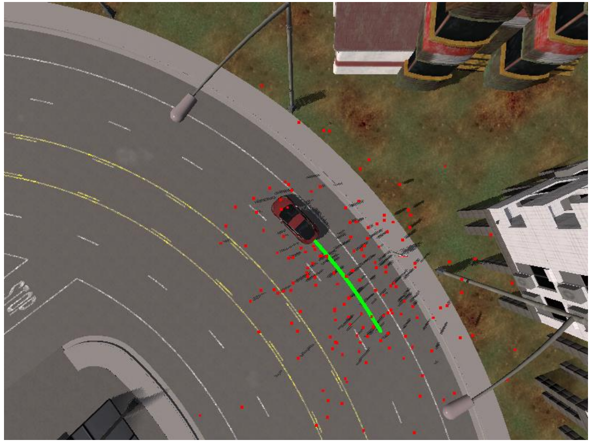


Figura 5: Erro de 10~20 metros

UNICAMP

- A localização robusta e precisa é fundamental e crucial para aplicações de CAVs.
- O GNSS(Como o GPS) tem algumas limitações:
    - Bloqueio de sinal
    - Erros de órbita de satélite
    - Atrasos troposféricos e ionosféricos
- Tais problemas causam um erro de localização variando de 5 a 30 metros.
- Para reduzir o erro de localização é proposto um mecanismo de fusão de dados para localização veicular cooperativa.

UNICAMP

Table 1. Summary of On-board Sensor-based Localisation Techniques.

Technique (Reference)	Sensors	Accuracy	Advantages	Disadvantages
Pure GPS **-**	GPS	~10m	Low cost	Low accuracy Poor signal availability
GPS/IMU in ECEF coordinates [26]	GPS & IMU	7.2m (RMSE)	Low cost IMU provides positioning during GPS signal blockage	Low accuracy Cumulative errors
Two-stage vision-based SLAM [27]	Camera	0.75m (Mean)	Low cost	Susceptible to illumination and observation angle
Stereovision odometry [28]	Camera	Up to 20.5m cumulative error over 166m distance	Low Cost	Low accuracy Cumulative errors
Vision-based localisation with lane detection [29]	Camera, GPS, IMU	0.73m (Mean)	Low cost	Susceptible to illumination and observation angle
Vision-based localisation with road marker detection [30]	Camera, GPS, IMU	0.58m, lat. 1.43m, long. (Mean)	Low cost	Susceptible to illumination and observation angle
Aerial Image-based localisation [16]	Camera, GPS, IMU	80% within 1m	Low cost	High errors
Microwave-Radar SLAM [32]	Microwave Radar	10.5m (Mean)	Low power requirements Low cost	Low accuracy
Short Range Radar SLAM [31]	Radar, GPS, IMU	0.07m, lat. 0.38m, long. (RMSE)	Low power requirements Low cost High accuracy	Low robustness to dynamic environments
Localising Ground Penetrating Radar [33]	LGPR, GPS, IMU	0.04m (RMSE)	Very high accuracy Robust to weather and illumination conditions	Lack of testing Sensitivity (e.g. to frost heave, thaw settlement) uncertain
LiDAR SLAM [35], [21], [36], [37], [38], [39]	LiDAR, GPS, IMU	0.017m, lat. 0.033m, long. (RMSE)	High accuracy Robust to changes in environment	High cost High power & processing requirements Sensitive to weather conditions
Camera localisation within LiDAR map [40]	Camera, IMU	0.14m, lat. 0.19m, long. (RMSE)	High accuracy Low cost	Requires environments to be mapped using a dedicated LiDAR vehicle Robustness
LRF based localisation [41]	GPS, IMU, LRF	3.098m (Mean)	Low cost	High errors
Ultrasonic SLAM [42]	Ultrasonic	(Not given)	Low power requirements Low cost	Low accuracy Long processing time

Kuutti, S., Fallah, S., Katsaros, K., Dianati, M., Mccullough, F., & Mouzakitis, A. (2018). ***A survey of the state-of-the-art localization techniques and their potentials for autonomous vehicle applications.*** IEEE Internet of Things Journal, 5(2), 829-846.

UNICAMP

Table 2. Summary of V2V Localisation Methods.

Method (Reference)	Sensors	No. of vehicles	Accuracy	Advantages	Disadvantages
VANET Multilateration [53]	GPS, V2V communication	5	3.30m (Mean)	Low Cost Does not rely on all vehicles being able to communicate	High Error
V2V and on-board sensor localisation [52]	GPS, V2V communication, ranging sensors	1800 & 1200 vehicles per hour on 1km of road	0.60m (Mean)	Does not rely on all vehicles being able to communicate	Requires on-board ranging sensors
COVEL approach [54]	GPS, odometry, V2V communication	6	50% within 1.09m	Low Cost	Assumes all vehicles equipped with GPS and V2V
VANET supported by stationary vehicles [55]	GPS, V2V communication	20 & 900	Up to 3.14m	Low Cost	Battery use while stationary Dependent on number of parked cars nearby
Multilateration with shared position estimates in VANET [56]	GPS, gas and brake pedal and steering wheel sensors, V2V communication	5	0.52 – 1.65m (MSE)	Low Cost Increased information sharing	Relies on the number of connected vehicles
Weighted V2V localisation based on intervehicle distance [57]	GPS, V2V communication	10	2.38m (Mean)	Improved robustness and accuracy	Relies on connected vehicles
Weighted localisation based on intervehicle distance and SNR [58]	GPS, V2V communication	20 - 200	0.25m-0.85m (Mean), based on network size	Improved robustness and accuracy	Relies on connected vehicles

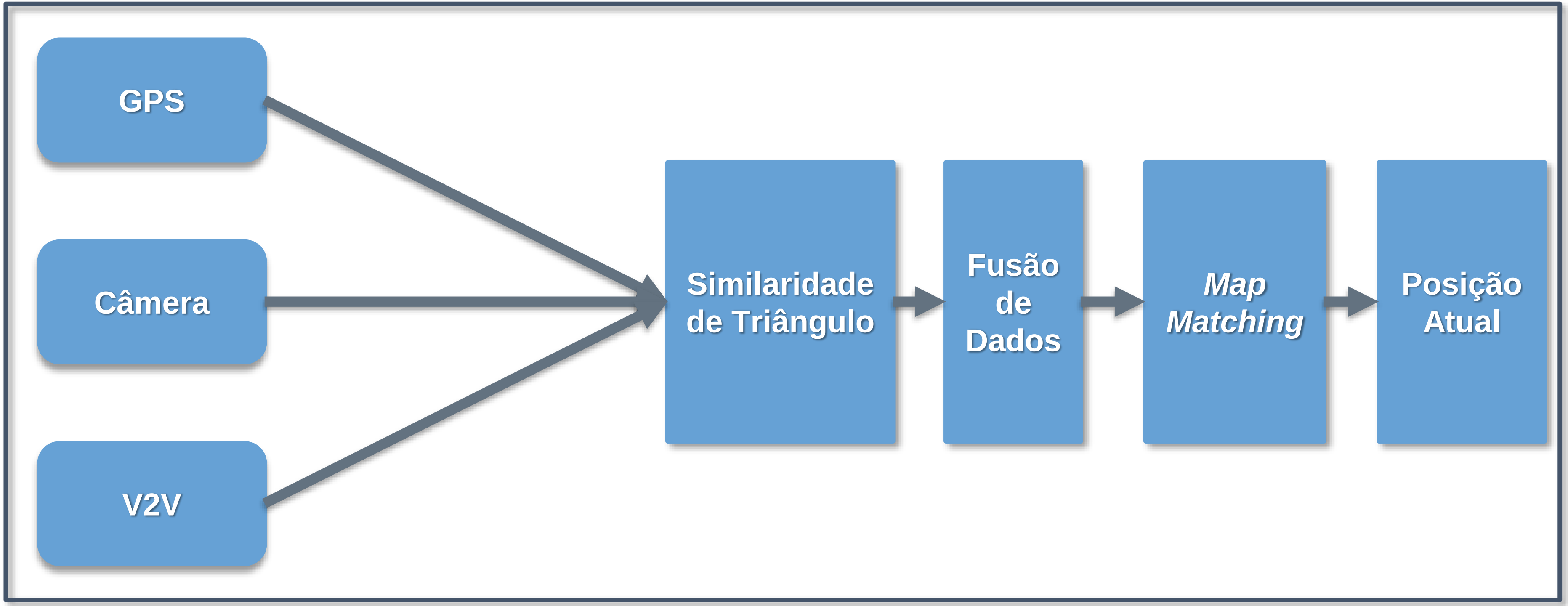
Kuutti, S., Fallah, S., Katsaros, K., Dianati, M., Mccullough, F., & Mouzakitis, A. (2018). ***A survey of the state-of-the-art localization techniques and their potentials for autonomous vehicle applications***. IEEE Internet of Things Journal, 5(2), 829-846.

Table 4. Localisation Techniques Adequate for Autonomous Vehicles.

Technique (Reference)	Sensors	Accuracy
Localising Ground Penetrating Radar [33]	LGPR, GPS, IMU	0.04m (RMSE)
LiDAR SLAM [35], [21], [36], [37], [38], [39]	LiDAR, GPS, IMU	0.017m, lat. 0.033m, long. (RMSE)
Camera localisation within LiDAR map [40]	Camera, IMU	0.14m, lat. 0.19m, long. (RMSE)
RF Infrastructure Localisation [64]	On-board UHF antenna	Up to 0.03m, lat.
5G-based Localisation [65]	5G communication device	99% below 0.2m at 100MHz

Kuutti, S., Fallah, S., Katsaros, K., Dianati, M., Mccullough, F., & Mouzakitis, A. (2018). ***A survey of the state-of-the-art localization techniques and their potentials for autonomous vehicle applications.*** IEEE Internet of Things Journal, 5(2), 829-846.

DUELAR


GPS
Câmera
V2V
Similaridade de Triângulo
Fusão de Dados
Map Matching
Posição Atual

DUELAR

- Fusão utilizando Filtro de Kalman Sem Cheiro (Unscented Kalman Filter - UKF)

$$\bar{x} = \sum_{i=0}^{2n} W_i^m \gamma_i$$

$$\bar{P} = \sum_{i=0}^{2n} W_i^c (\gamma_i - \bar{x})\,(\gamma_i - \bar{x})^T + Q$$

$$\mu_Z = \sum_{i=0}^{2n} W_i^m Z_i$$

DUELAR

$$P_Z = \sum_{i=0}^{2n} W_i^c (Z_i - \mu_Z)(Z_i - \mu_Z)^T + R$$

$$K = \left[\sum_{i=0}^{2n} W_i^c (\gamma_i - \bar{x})(Z_i - \mu_Z)^T \right] P_Z^{-1}$$

$$x = \bar{x} + K(z - \mu_Z)$$

$$P = \bar{P} - K P_Z K^T$$

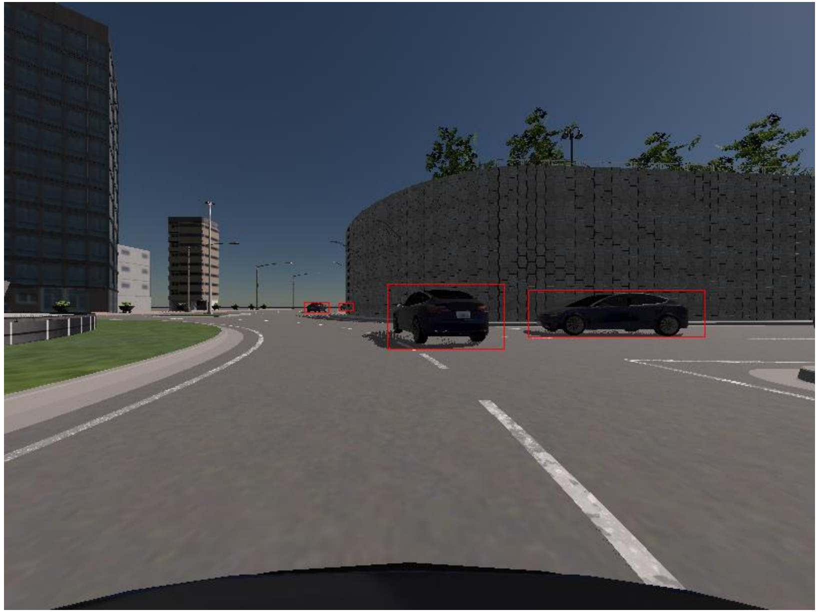


Figura 6: Detecção do *Bounding Box* dos CAVs

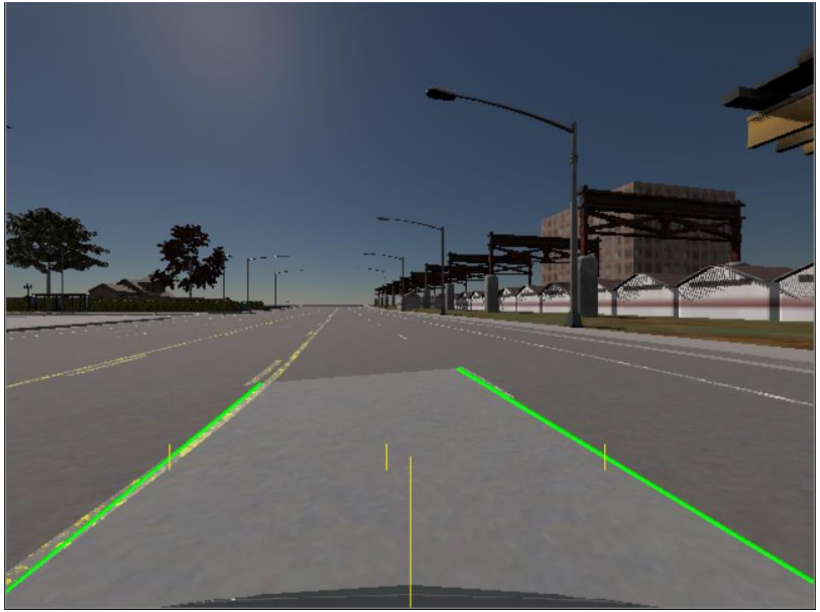
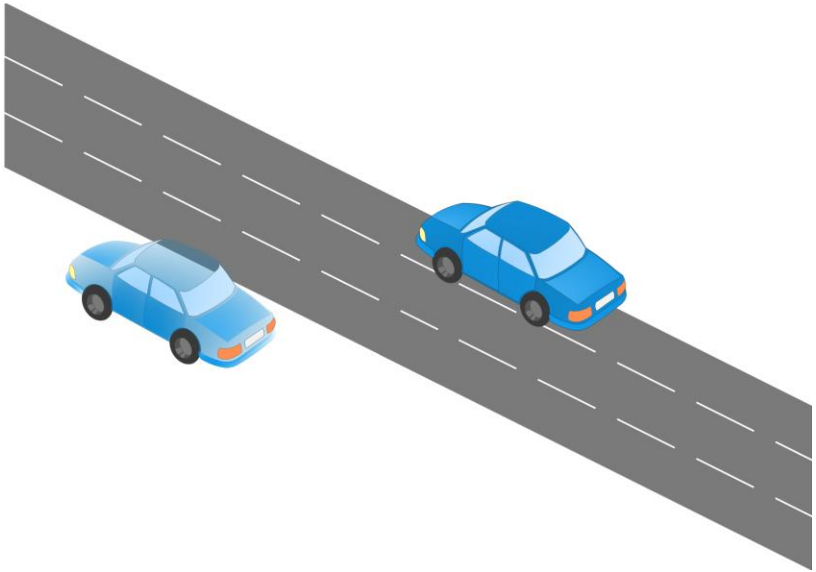


Figura 7: Detecção da Faixa

Transformada
de Hough



Algoritmo 1: Distância mínima entre um ponto e uma linha

Entrada
X_1, Y_1, X_2, Y_2 //Pontos que definem a faixa
X_3, Y_3 //Ponto estimado pelo UKF
Saída
X'_3, Y'_3 //Novo ponto dentro da faixa
início
  Px $\leftarrow X_2 - X_1$
  Py $\leftarrow Y_2 - Y_1$
  U $\leftarrow ((X_3 - X_1) * Px + (Y_3 - Y_1) * Py)/(Px^2 + Py^2)$
  se $U > 1$ **então**
    U $\leftarrow$ 1
  senão
    se $u < 0$ **então**
      U $\leftarrow$ 0
  $X'_3 \leftarrow X_1 + U * Px$
  $Y'_3 \leftarrow Y_1 + U * Py$
  Dx $\leftarrow X'_3 - X_3$
  Dy $\leftarrow Y'_3 - Y_3$
  Dist $\leftarrow \sqrt{(Dx^2 + Dy^2)}$

Resultados

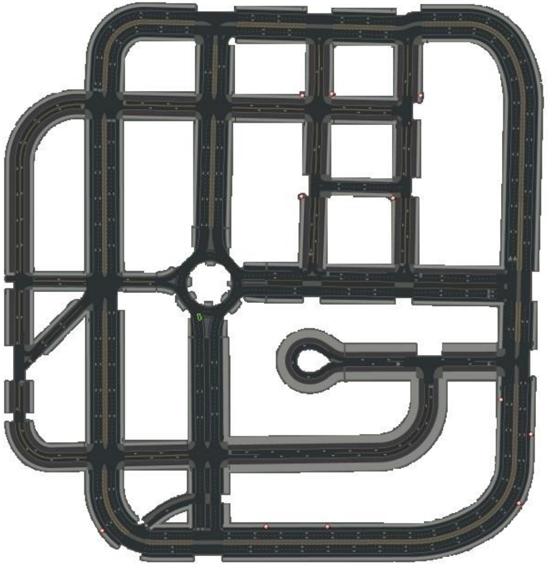


Figura 8: Topologia do Cenário Carla *Town* 3

Parâmetro	Valor
Densidade de veículos	50 veículos
Frequência do canal	5.89 GHz
Potência de transmissão	2.2 mW
Sensibilidade	-94 dBm
Raio de comunicação	300 m
Taxa de bits	6 Mbps
Frequência de GPS	10 Hz
Erro de GPS	5 - 10 m
Tamanho do cenário	600 m X 600 m
Tempo de simulação	200 s
α, β, κ	0.001, 2, 0

Tabela 1: Parâmetros de Simulação

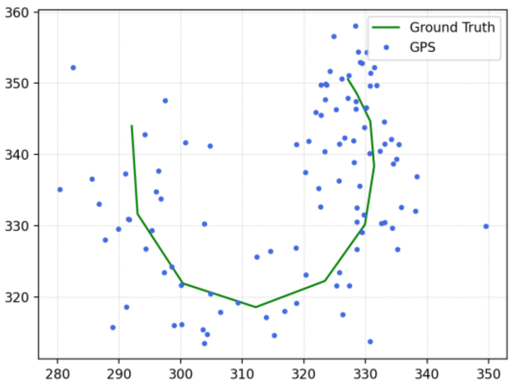


Figura 9: GPS

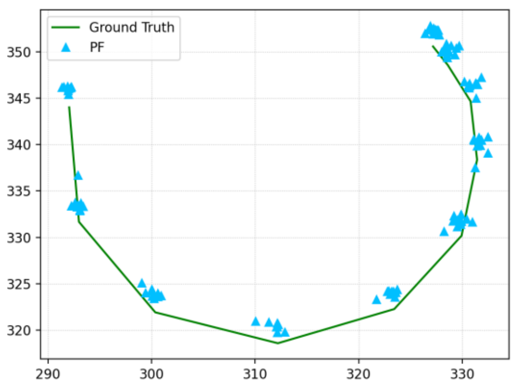


Figura 10: Filtro de Partículas

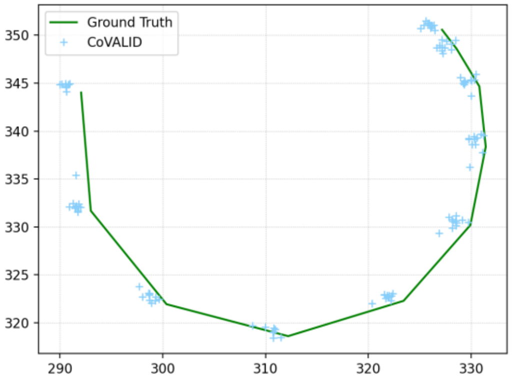


Figura 11: CoVaLID

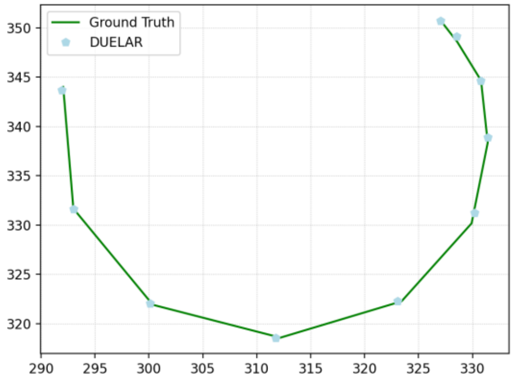


Figura 12: DUELAR

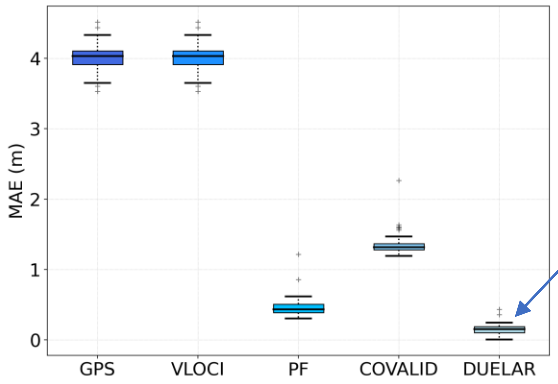
Avaliação de Desempenho (DUEL)

Métricas Avaliadas

- MAE (Mean Absolute Error)
- Comparação entre a localização estimada e a localização verdadeira.
- Mesmo peso para todos os erros.
- Um menor resultado significa melhor precisão.

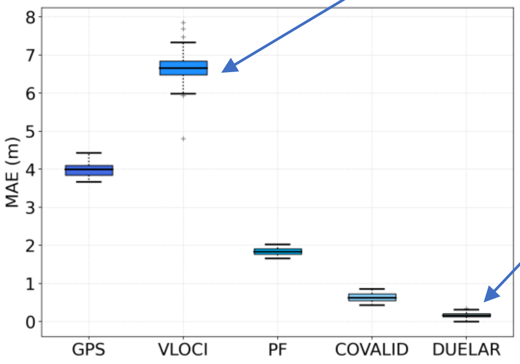
$$MAE = \frac{1}{n}\sum_{j=1}^{n}\left|y_j - \hat{y}_j\right|$$

Pior Resultado



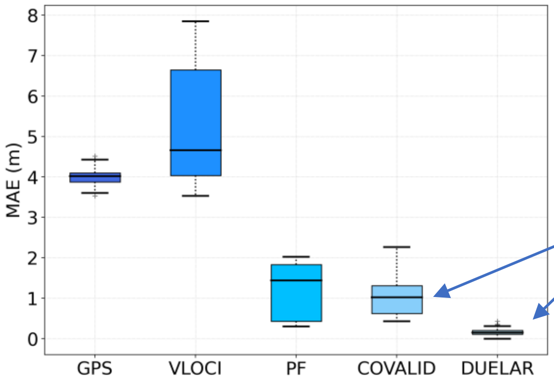
43 cm

Figura 13: Latitude (X)



36 cm

Figura 141: Longitude (Y)



85%

Figura 15: Ambos os eixos

Avaliação de Desempenho (DUEL)

Métricas Avaliadas

- RMSE (Root-Mean-Square Error)
- Comparação entre a localização estimada e a localização verdadeira.
- Atribui um peso alto a erros significativos.
- Um menor resultado significa melhor precisão.
- O valor de RMSE pode ser igual ou maior que o MAE.

$$RMSE = \sqrt{\frac{1}{n}\sum_{j=1}^{n}\left(y_j - \hat{y}_j\right)^2}$$

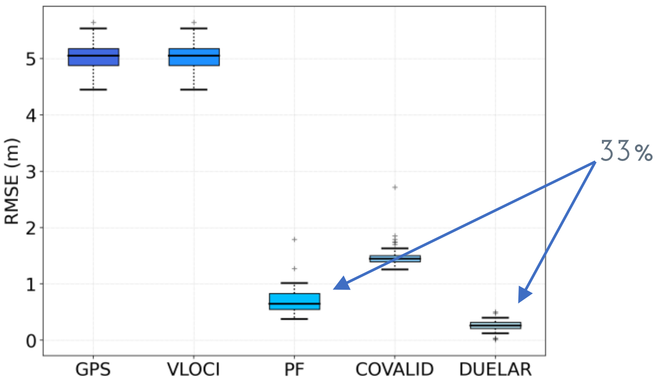


Figura 16: Latitude (X)

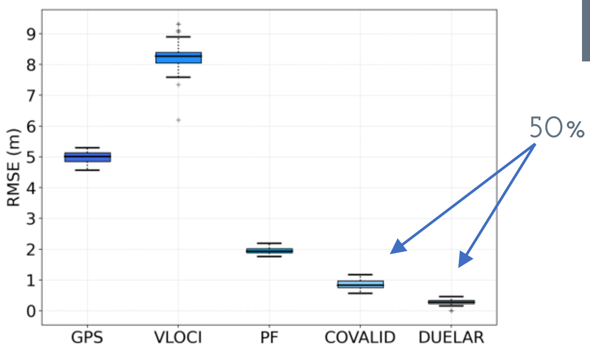


Figura 17: Longitude (Y)

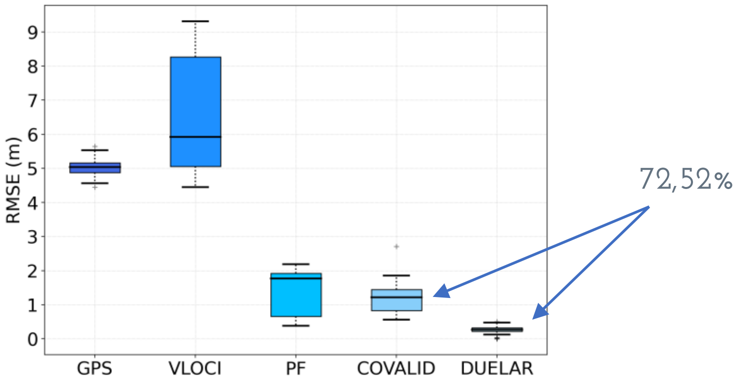
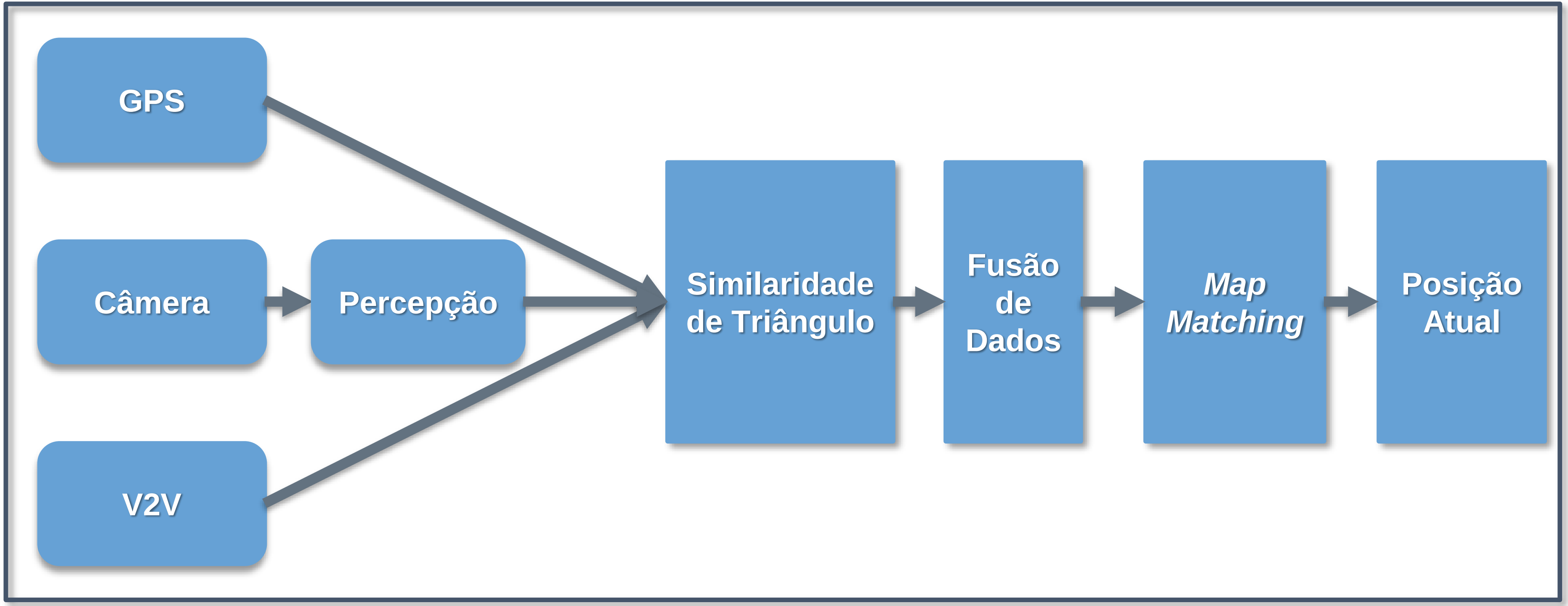


Figura 18: Ambos os eixos

Próximos Passos


GPS
Câmera
Percepção
V2V
Similaridade de Triângulo
Fusão de Dados
Map Matching
Posição Atual

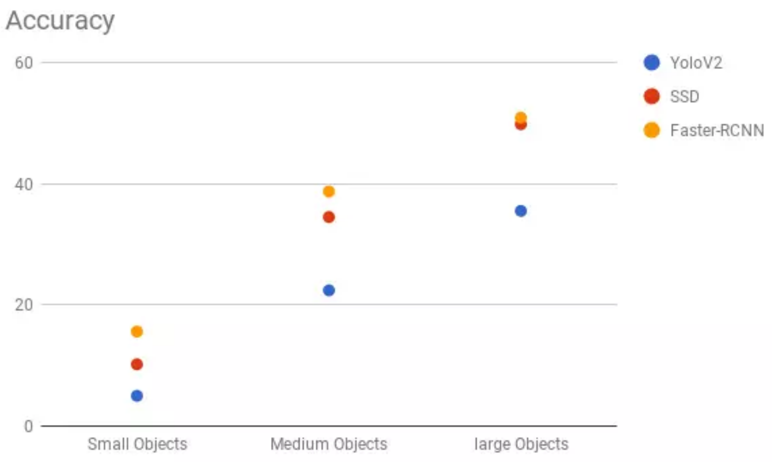


Figura 19: YOLO x SSD x Faster-RCNN

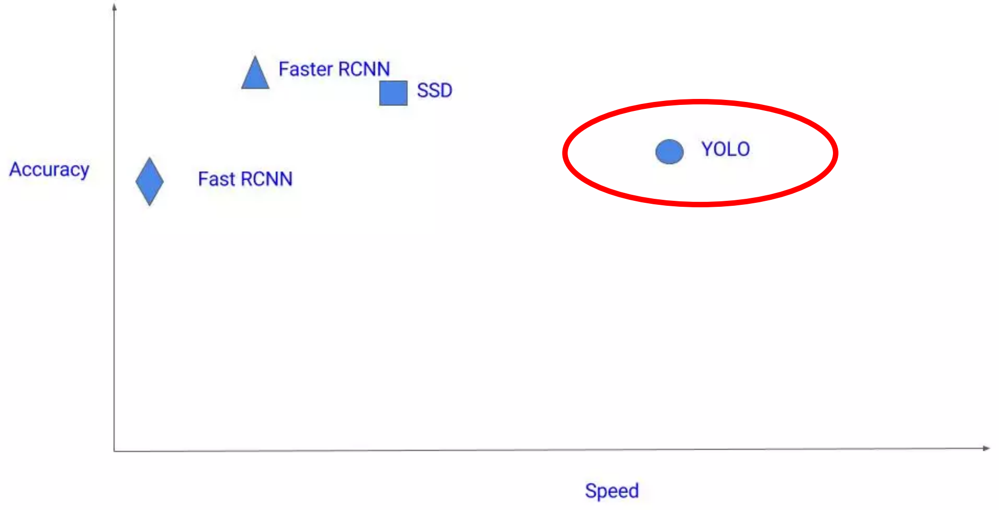


Figura 20: Acurácia X Velocidade de Resposta

Figura 21: Carla Frame 407

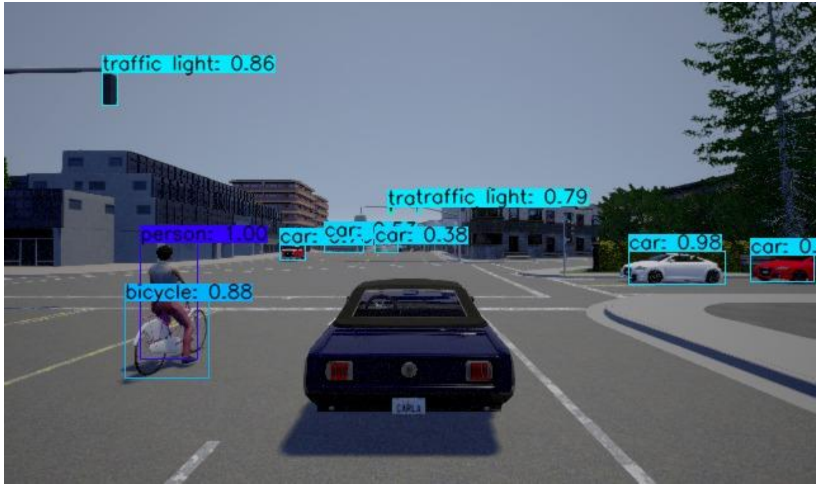
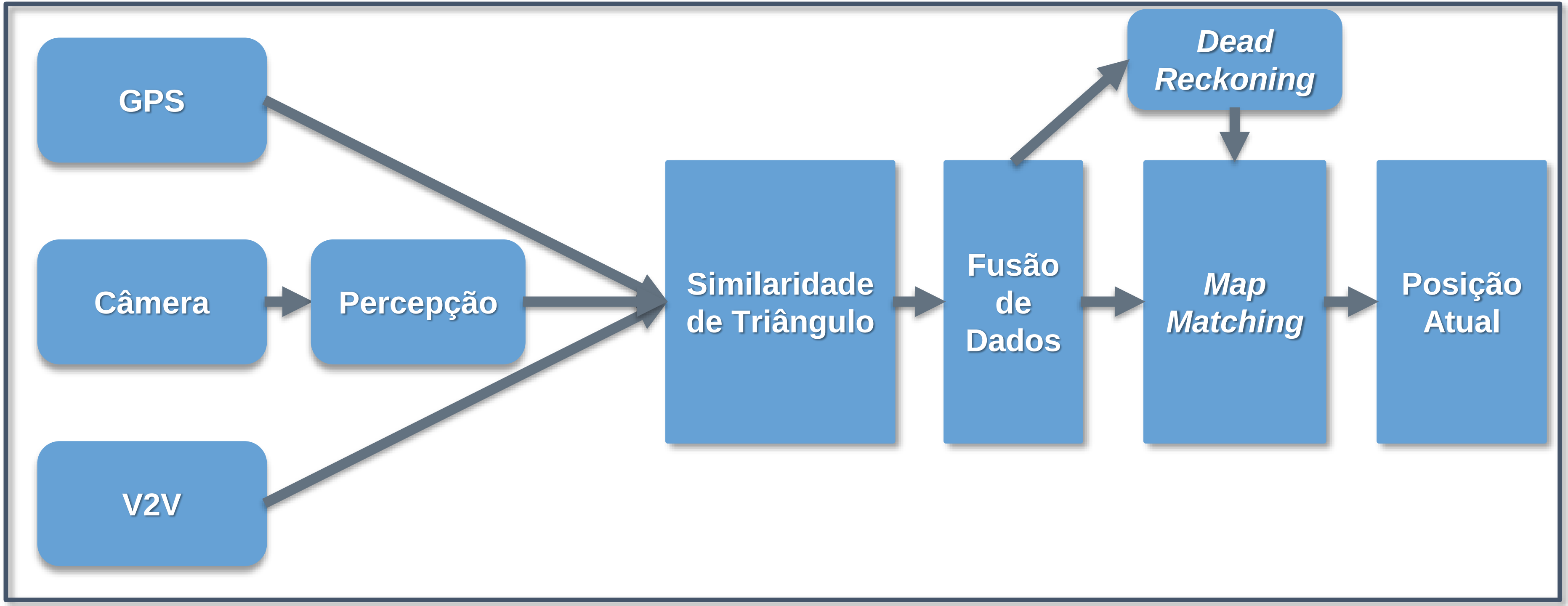


Figura 22: Carla Frame 407 + YOLO v3

Figura 23: Carla Frame 518

Figura 24: Carla Frame 518 + YOLO v3

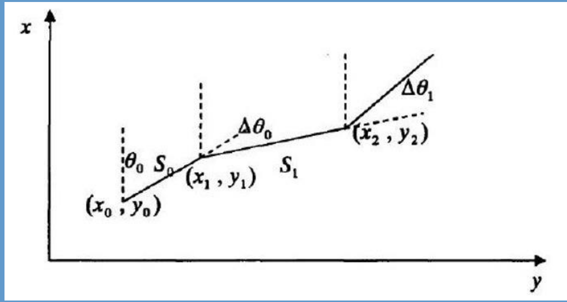

GPS
Câmera
Percepção
V2V
Similaridade de Triângulo
Fusão de Dados
Dead Reckoning
Map Matching
Posição Atual

Dead Reckoning

- Estimar as próximas posições de um objeto móvel de acordo com sua movimentação.
- O método funciona bem para objetos que se movem em velocidades baixas.

$$X_n = X_{n-1} + S_{n-1} \sin \theta_{n-1}$$

$$Y_n = Y_{n-1} + S_{n-1} \cos \theta_{n-1}$$

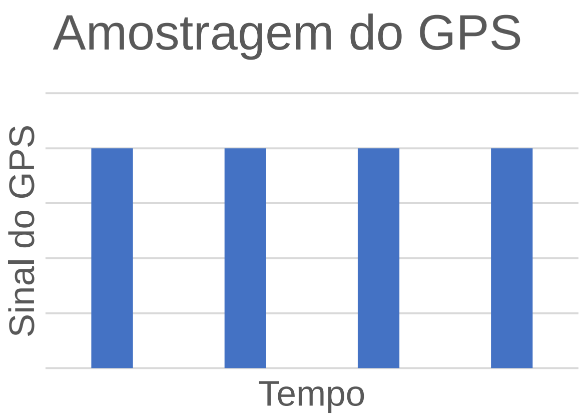


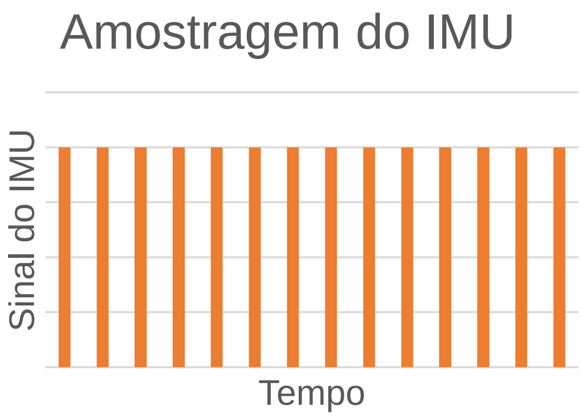
Dead Reckoning + Carla

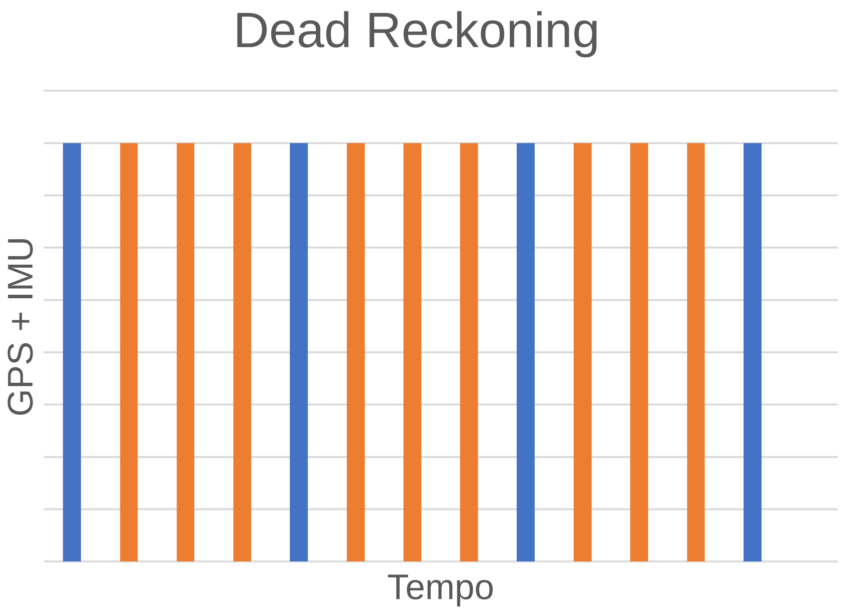
$$S_{n-1} = v_{n-1} \times dt_{n-1}$$

$$X_n = X_{n-1} + S_{n-1} \sin \theta_{n-1}$$

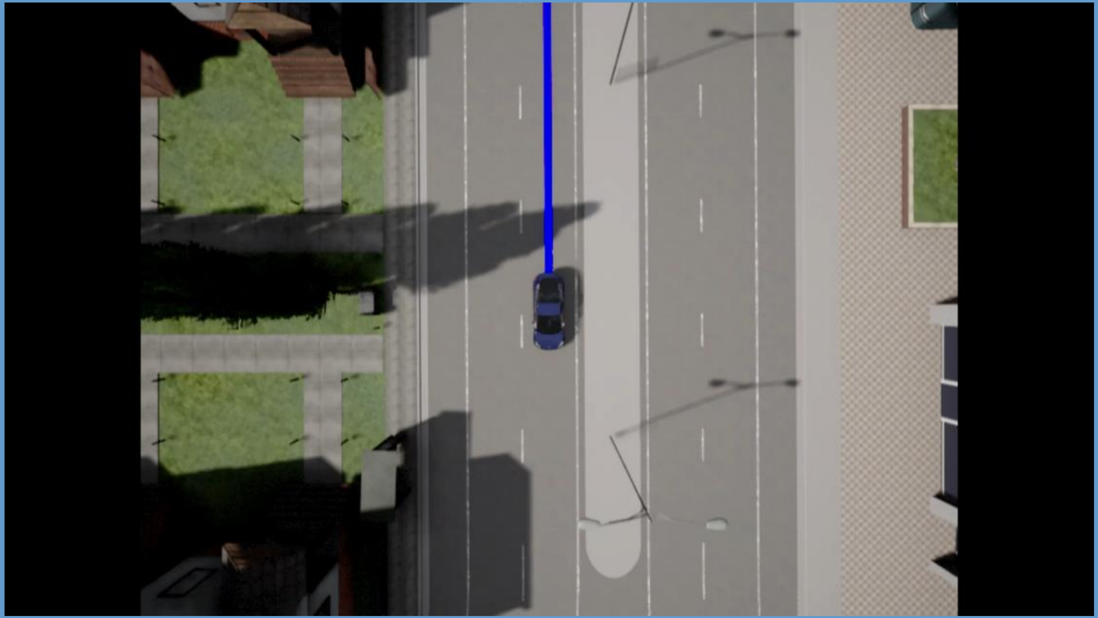
$$Y_n = Y_{n-1} + S_{n-1} \cos \theta_{n-1}$$

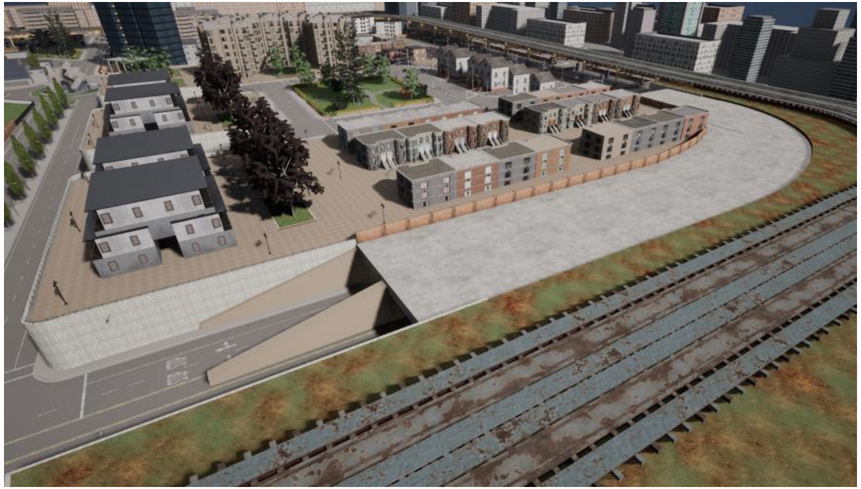

Amostragem do GPS
Sinal do GPS
Tempo

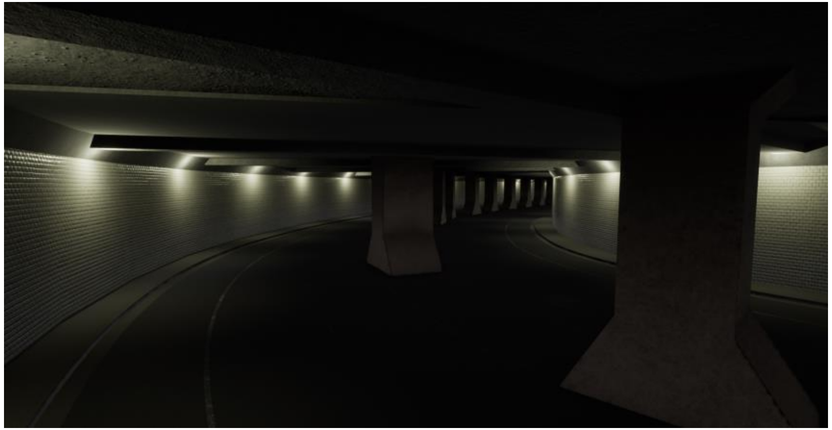

Amostragem do IMU
Sinal do IMU
Tempo


Dead Reckoning
GPS + IMU
Tempo

Dead Reckoning + Carla







- Adaptar o filtro de histograma para o cenário
- Implementar diferentes sistemas de detecção de objetos
    - *You Only Look Once* (YOLO) v3 ✔
- Adicionar o *Dead Reckoning* para cenário de túnel ✔
- Desenvolver um *Motion Planner* baseado em GPS
- Avaliar os resultados de localização em novos cenários

Motion Planner

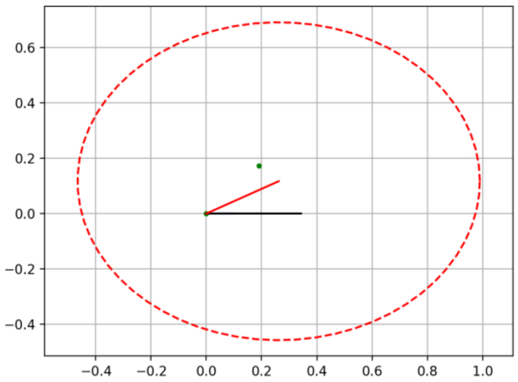


Figura 25: Extended Kalman Filter

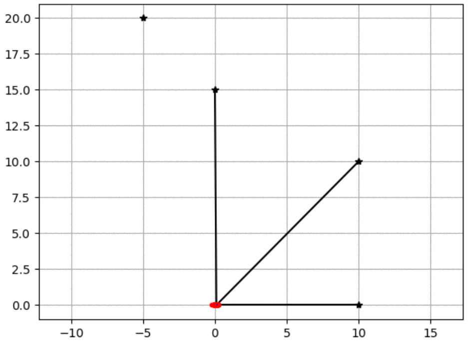


Figura 26: Particle Filter

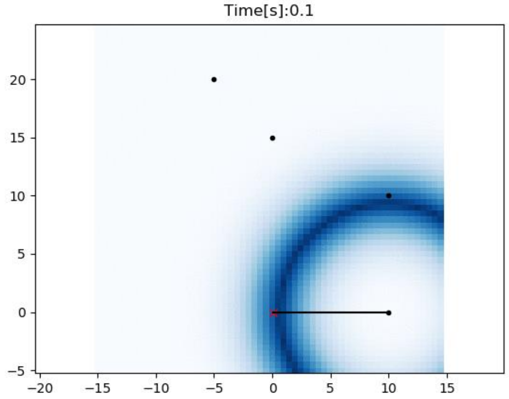


Figura 27: Histogram Filter

Obrigado!

Dúvidas?

Wellington Viana Lobato Junior

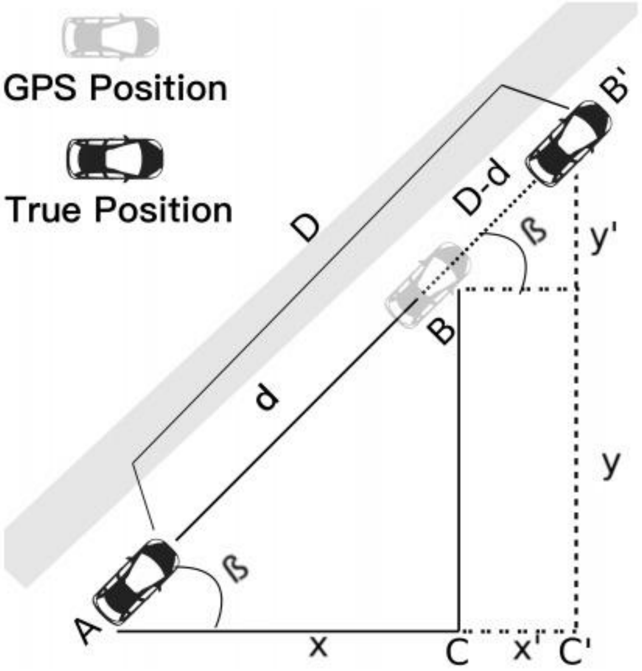
wellington@lrc.ic.unicamp.br

http://www.lrc.ic.unicamp.br/~wellington/

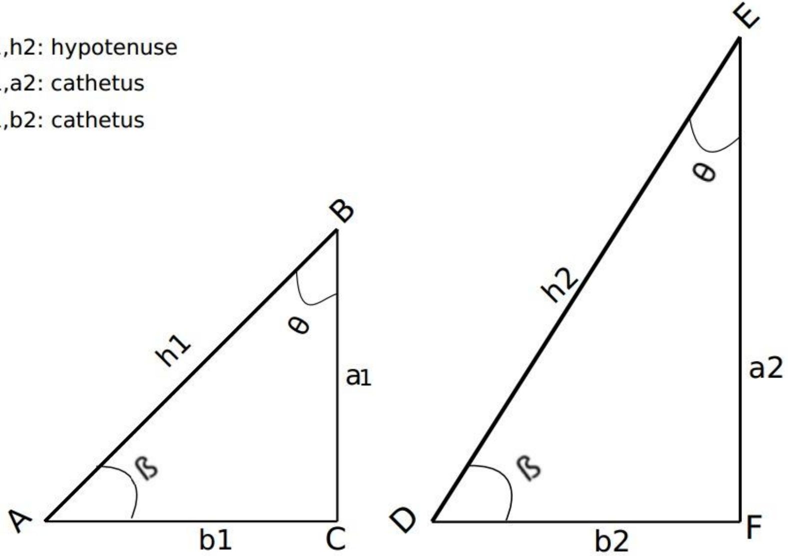
Computer Networks Laboratory

FAPESP

UNICAMP



h1,h2: hypotenuse
a1,a2: cathetus
b1,b2: cathetus



(a) ABC Triangle (b) DEF Triangle