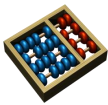


# Mecanismo Eficiente de Localização Cooperativa para Veículos Autônomos Conectados

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Orientador: Prof. Dr. Leandro A. Villas (UNICAMP)

Coorientador: Prof. Dr. Denis L. Rosário (UFPA)



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# Introdução



## Visão Geral

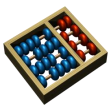
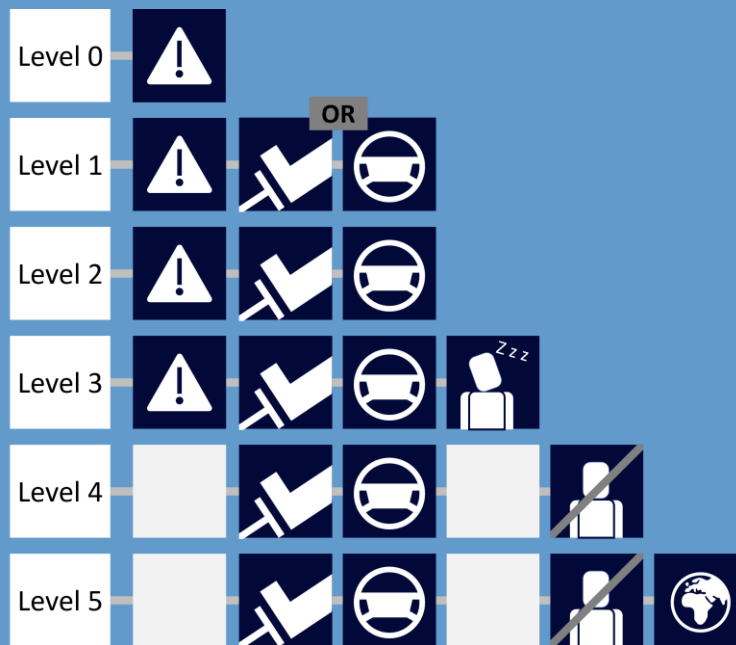
- Veículos Autônomos Conectados (Connected Autonomous Vehicle - CAV)
- Níveis de Direção Autônoma SAE(Sociedade dos Engenheiros Automotivos).
- O funcionamento dos CAVs considera três camadas: Sensoriamento, Percepção e Decisão.

## Motivação

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

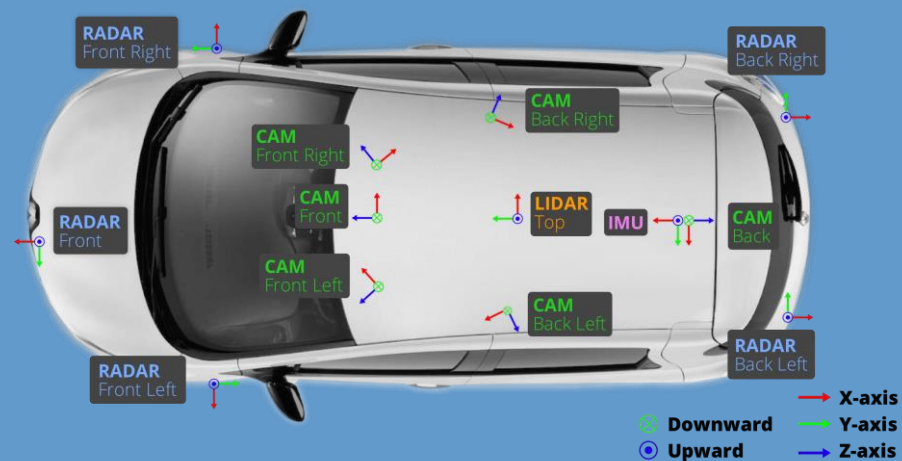


## Níveis de Automação SAE (Society of Automotive Engineers)



## Componentes Fundamentais

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



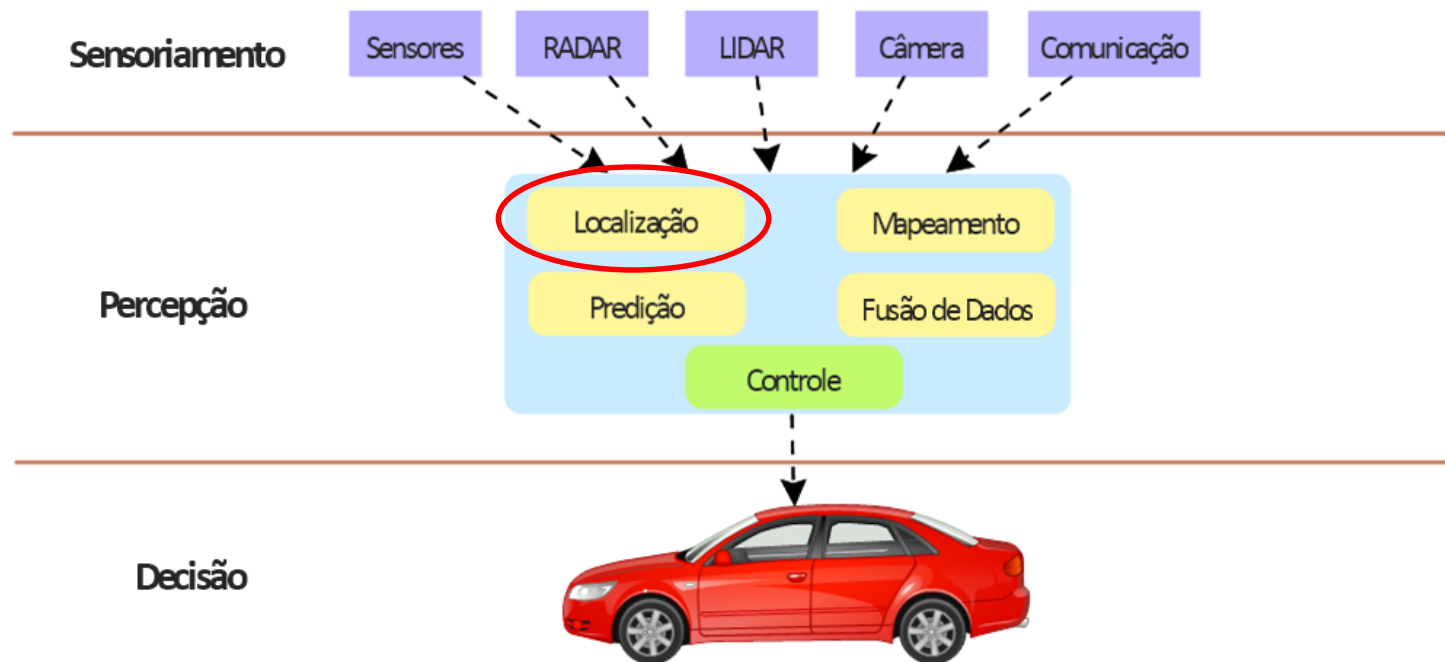


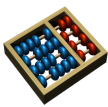
Figura 1: Arquitetura Funcional de um CAV



## 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	$\geq 10$	-
Overtaking vehicle warning			2-10	100	10-5000	30
Lane change assistance			2-10	100	10-5000	30
Cooperative glare reduction			2	100	$\geq 10$	-
Merging traffic turn collision risk warning			2-10	100	10-5000	-
Cooperative collision warning			10	100	$\geq 10$	30
Cooperative navigation			1-10	100	10-2000	<100
Adaptive cruise control			1-10	100	10-2000	<100
Highway platooning			$\geq 2$	$\leq 10$	$\geq 10$	30
Emergency or slow vehicle warning	Event-driven		10	100	$\geq 10$	-
Wrong way driving warning			$\geq 1$ & $\leq 10$	100	1-10	<100
Stationary vehicle warning			$\geq 1$ & $\leq 10$	100	1-10	<500
Traffic condition warning			1-10	100	1-10	<500
Intersection warning			10	100	10	<100
Post-crash warning			10	100	$\geq 10$	<100
Cooperative adaptive cruise control			1-10	100-300	10-2000	30





# Modelagem do GPS

- Atender requisitos das aplicações de CAVs

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

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



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





Figura 2: Erro de 1 metro

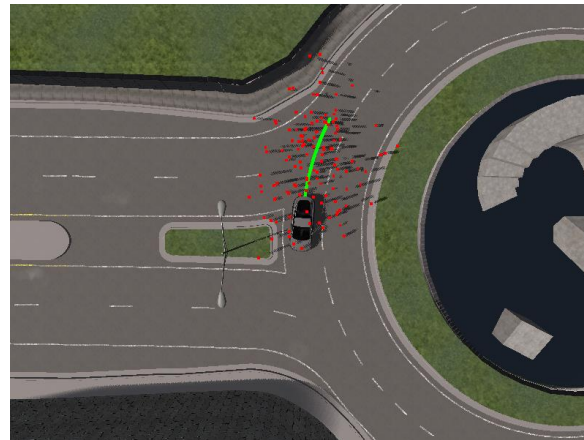


Figura 3: Erro de 2~5 metros



Figura 4: Erro de 5~10 metros

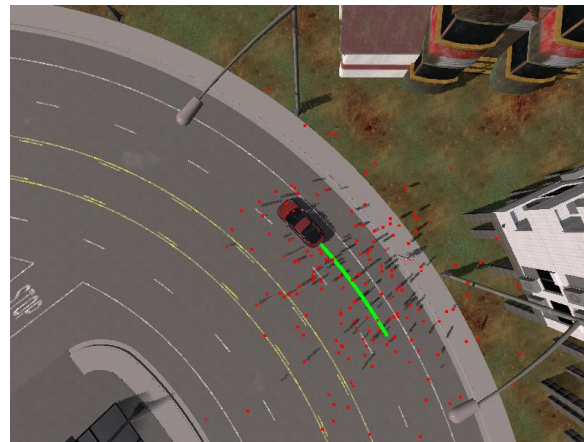


Figura 5: Erro de 10~20 metros



- 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.



*Table 4. Localisation Techniques Adequate for Autonomous Vehicles.*

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



Table 2. Summary of V2V Localisation Methods.

Method (Reference)	Sensors	No. of vehicles	Accuracy	Advantages	Disadvantages
<b>VANET Multilateration</b> [53]	GPS, V2V communication	5	3.30m (Mean)	Low Cost Does not rely on all vehicles being able to communicate	High Error
<b>V2V and on-board sensor localisation</b> [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
<b>COVEL approach</b> [54]	GPS, odometry, V2V communication	6	50% within 1.09m	Low Cost	Assumes all vehicles equipped with GPS and V2V
<b>VANET supported by stationary vehicles</b> [55]	GPS, V2V communication	20 & 900	Up to 3.14m	Low Cost	Battery use while stationary Dependent on number of parked cars nearby
<b>Multilateration with shared position estimates in VANET</b> [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
<b>Weighted V2V localisation based on intervehicle distance</b> [57]	GPS, V2V communication	10	2.38m (Mean)	Improved robustness and accuracy	Relies on connected vehicles
<b>Weighted localisation based on intervehicle distance and SNR</b> [58]	GPS, V2V communication	20 - 200	0.25m-0.85m (Mean), based on network size	Improved robustness and accuracy	Relies on connected vehicles

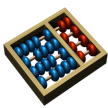


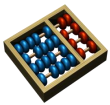
Table 1. Summary of On-board Sensor-based Localisation Techniques.

Technique (Reference)	Sensors	Accuracy	Advantages	Disadvantages
<b>Pure GPS</b> -	GPS	~10m	Low cost	Low accuracy Poor signal availability
<b>GPS/IMU in ECEF coordinates</b> [26]	GPS & IMU	7.2m (RMSE)	Low cost IMU provides positioning during GPS signal blockage	Low accuracy Cumulative errors
<b>Two-stage vision-based SLAM</b> [27]	Camera	0.75m (Mean)	Low cost	Susceptible to illumination and observation angle
<b>Stereovision odometry</b> [28]	Camera	Up to 20.5m cumulative error over 166m distance	Low Cost	Low accuracy Cumulative errors
<b>Vision-based localisation with lane detection</b> [29]	Camera, GPS, IMU	0.73m (Mean)	Low cost	Susceptible to illumination and observation angle
<b>Vision-based localisation with road marker detection</b> [30]	Camera, GPS, IMU	0.58m, lat. 1.43m, long. (Mean)	Low cost	Susceptible to illumination and observation angle
<b>Aerial Image-based localisation</b> [16]	Camera, GPS, IMU	80% within 1m	Low cost	High errors

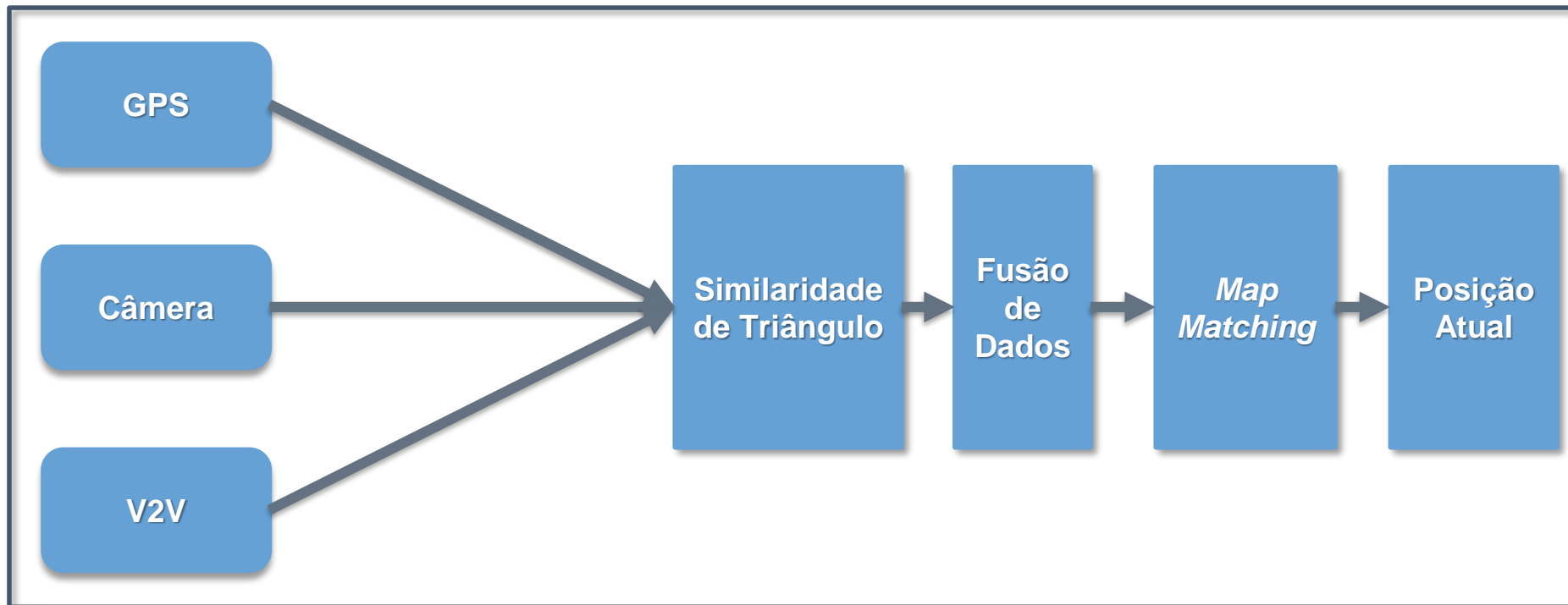
<b>Microwave-Radar SLAM</b> [32]	Microwave Radar	10.5m (Mean)	Low power requirements Low cost	Low accuracy
<b>Short Range Radar SLAM</b> [31]	Radar, GPS, IMU	0.07m, lat. 0.38m, long. (RMSE)	Low power requirements Low cost High accuracy	Low robustness to dynamic environments
<b>Localising Ground Penetrating Radar</b> [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
<b>LiDAR SLAM</b> [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
<b>Camera localisation within LiDAR map</b> [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
<b>LRF based localisation</b> [41]	GPS, IMU, LRF	3.098m (Mean)	Low cost	High errors
<b>Ultrasonic SLAM</b> [42]	Ultrasonic	(Not given)	Low power requirements Low cost	Low accuracy Long processing time



# DUELAR







DUEL

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

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

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

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



DUEL

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

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

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

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



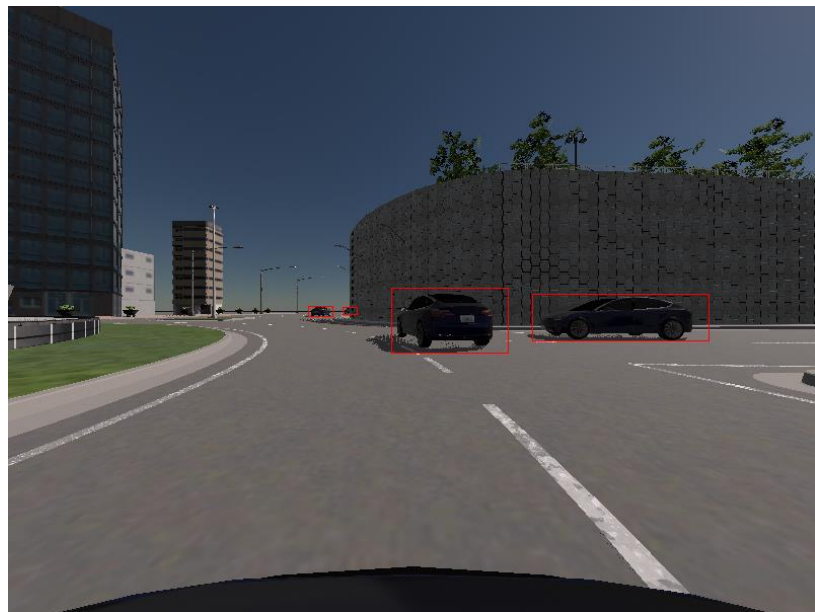


Figura 6: Detecção do *Bounding Box* dos CAVs

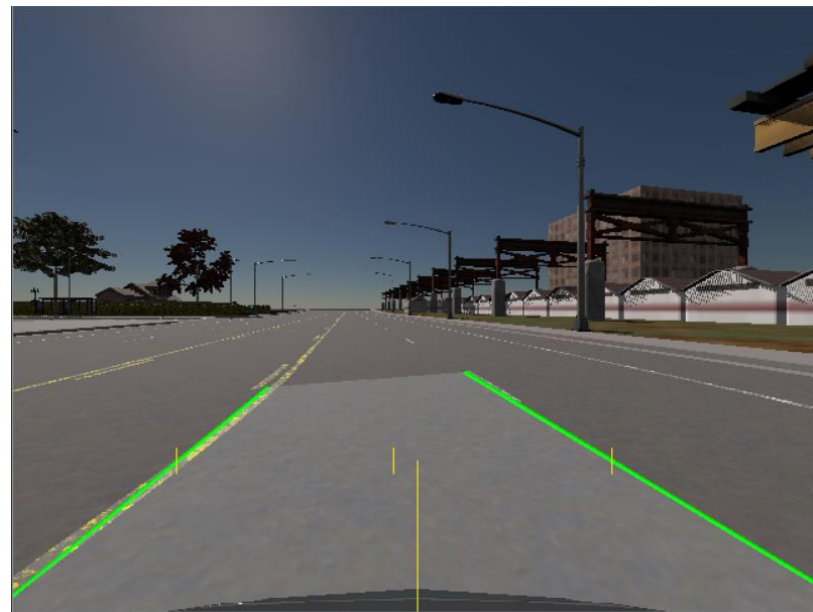
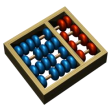
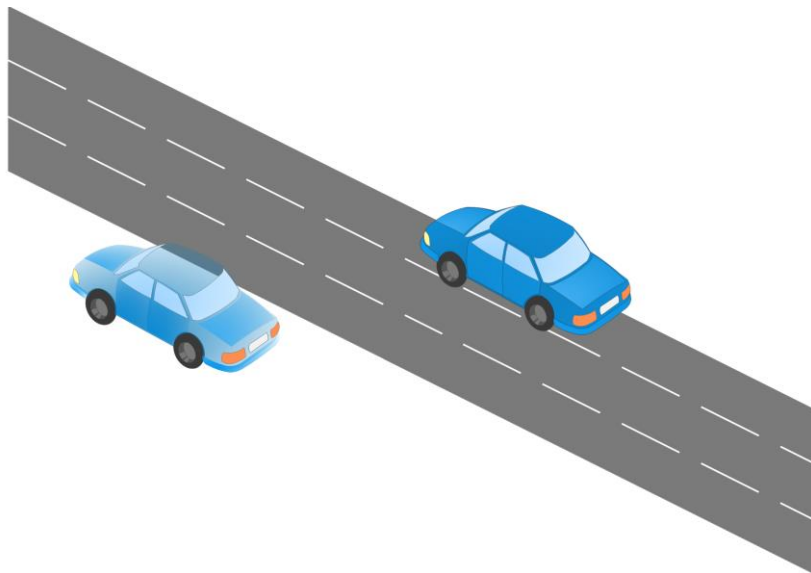


Figura 7: Detecção da Faixa






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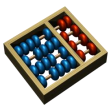
**Algoritmo 1:** Distância mínima entre um ponto e uma linha
 

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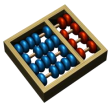
```

1  Entrada
2   $X_1, Y_1, X_2, Y_2$  //Pontos que definem a faixa
3   $X_3, Y_3$  //Ponto estimado pelo UKF
4  Saída
5   $X'_3, Y'_3$  //Novo ponto dentro da faixa
6  início
7     $Px \leftarrow X_2 - X_1$ 
8     $Py \leftarrow Y_2 - Y_1$ 
9     $U \leftarrow ((X_3 - X_1) * Px + (Y_3 - Y_1) * Py) / (Px^2 + Py^2)$ 
10   se  $U > 1$  então
11      $U \leftarrow 1$ 
12   senão
13     se  $u < 0$  então
14        $U \leftarrow 0$ 
15    $X'_3 \leftarrow X_1 + U * Px$ 
16    $Y'_3 \leftarrow Y_1 + U * Py$ 
17    $Dx \leftarrow X'_3 - X_3$ 
18    $Dy \leftarrow Y'_3 - Y_3$ 
19    $Dist \leftarrow \sqrt{Dx^2 + Dy^2}$ 
  
```

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# Resultados



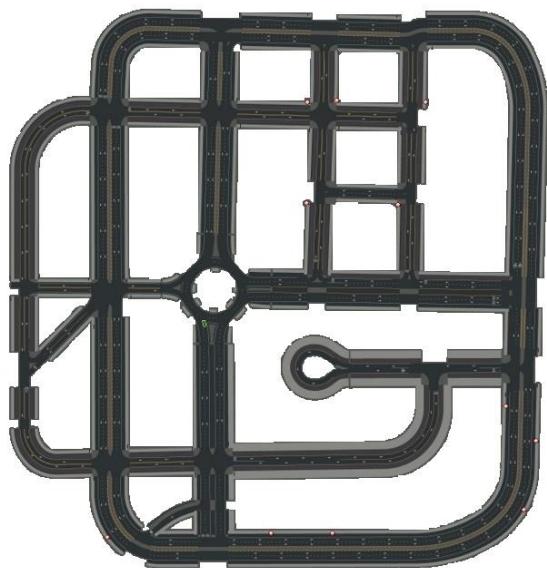
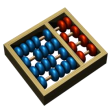


Figura 8: Topologia do Cenário Carla Town 3

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
$\alpha, \beta, \kappa$	0.001, 2, 0

Tabela 1: Parâmetros de Simulação



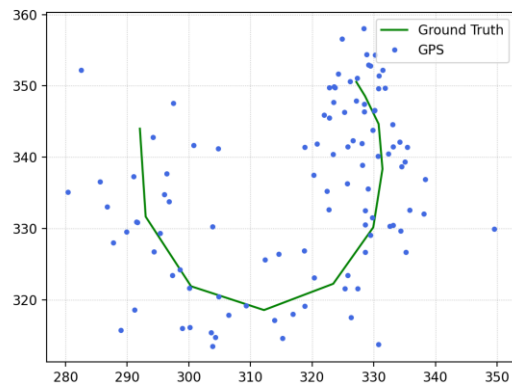


Figura 9: GPS

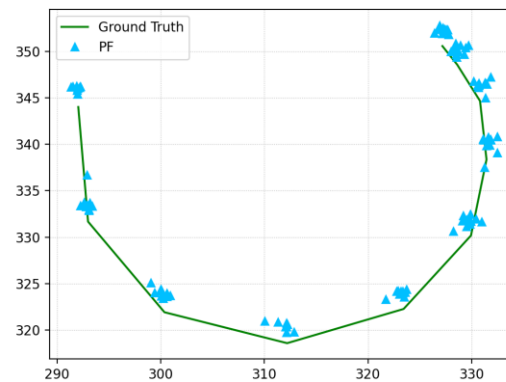


Figura 10: Filtro de Partículas

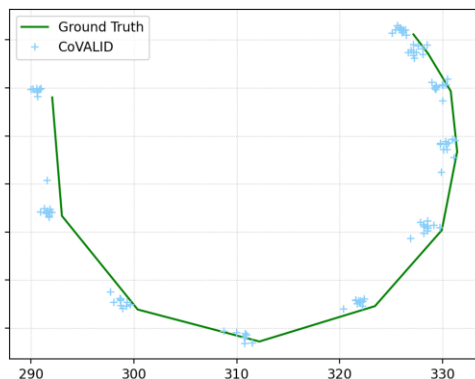


Figura 11: CoVaLiD

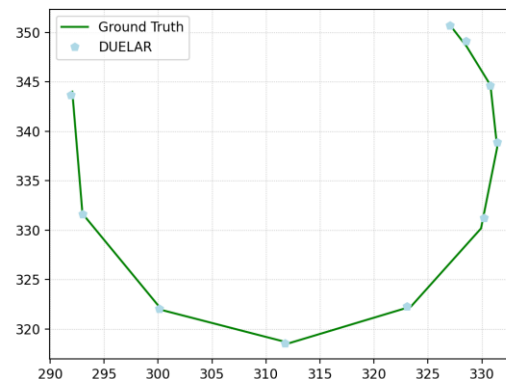


Figura 12: DUELAR





## 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.

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



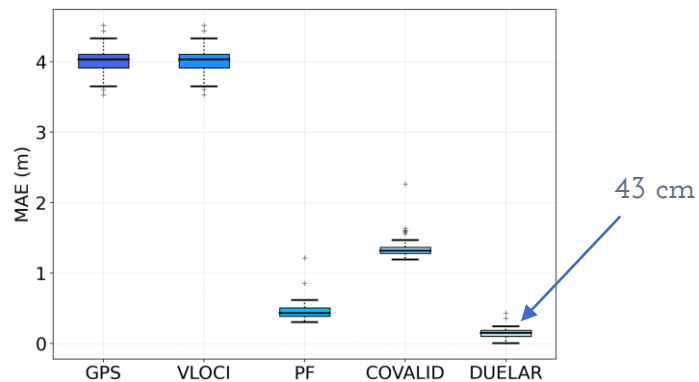


Figura 13: Latitude (X)

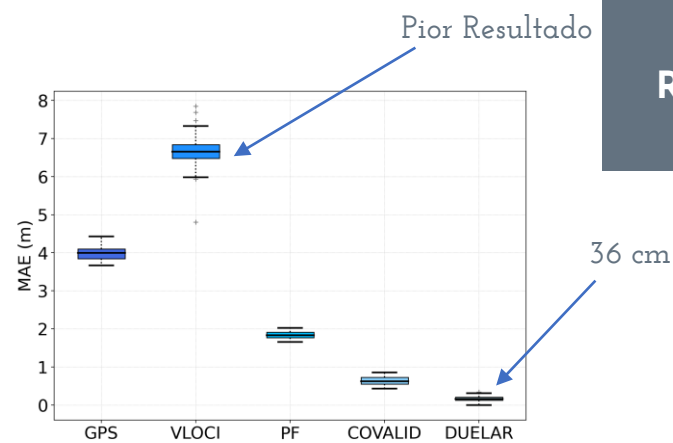


Figura 14: Longitude (Y)

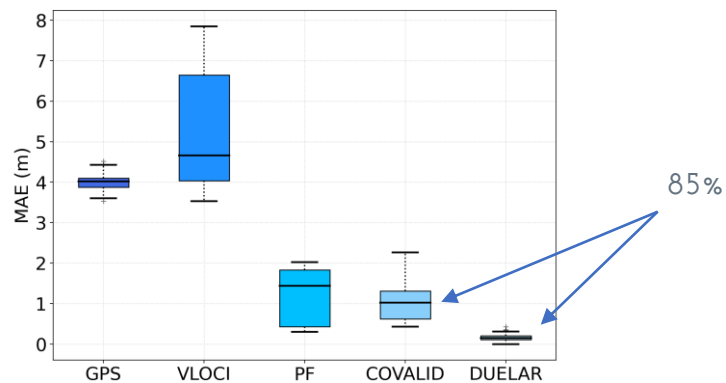
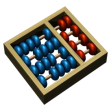


Figura 15: Ambos os eixos

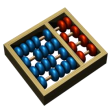


## Avaliação de Desempenho (DUEL)

### 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.

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



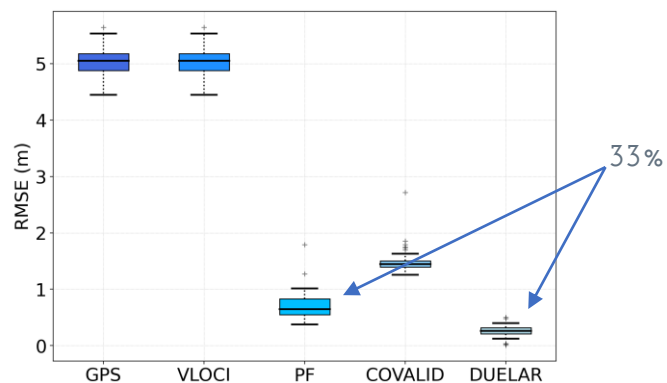


Figura 16: Latitude (X)

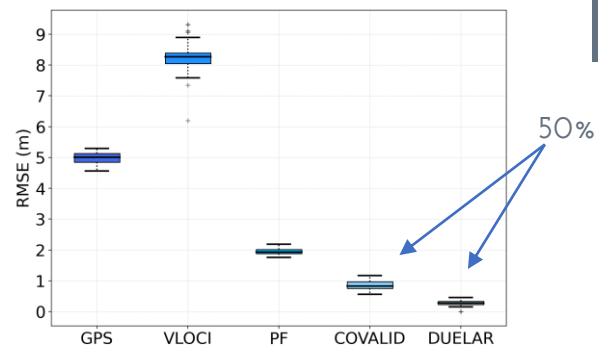


Figura 17: Longitude (Y)

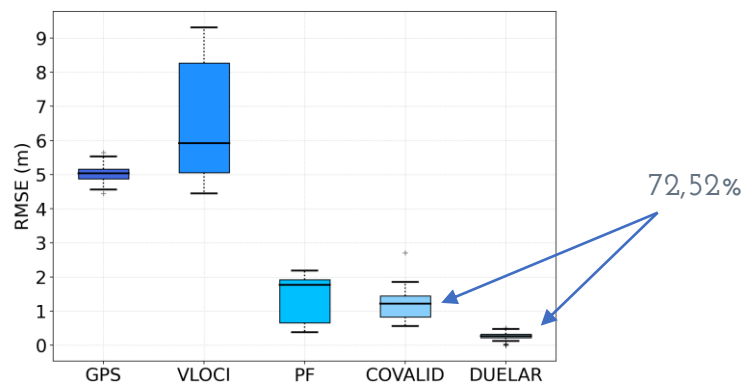
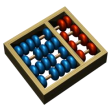
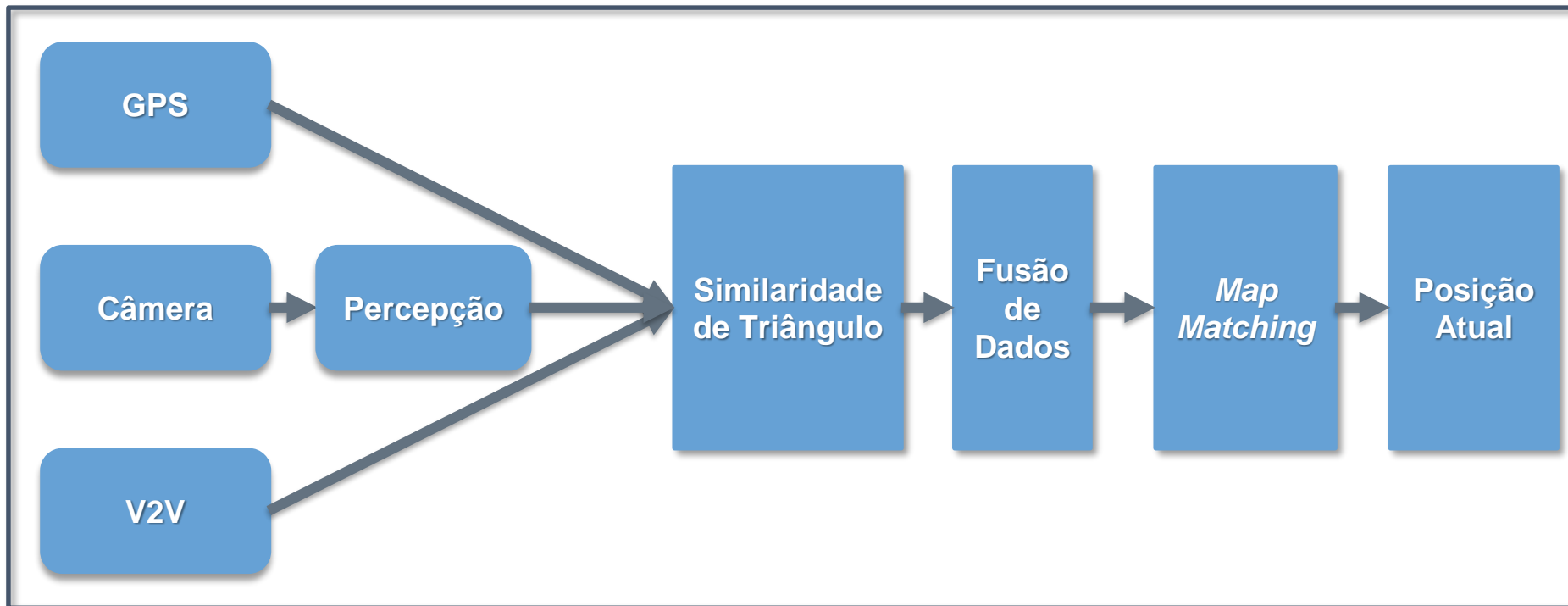


Figura 18: Ambos os eixos



# Próximos Passos





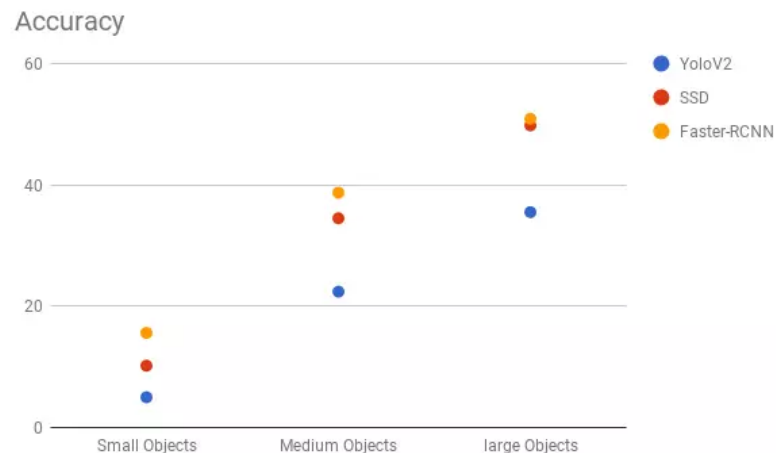


Figura 19: YOLO x SSD x Faster-RCNN

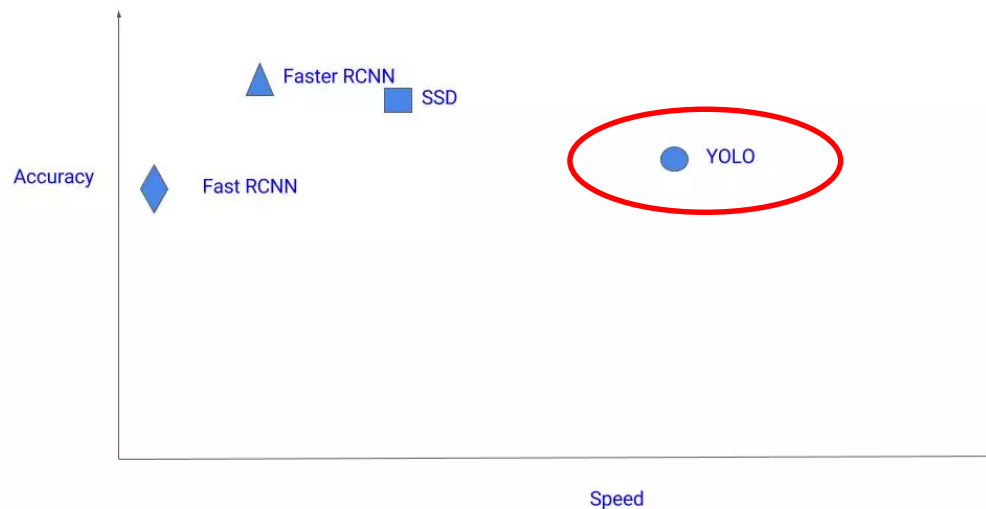


Figura 20: Acurácia X Velocidade de Resposta

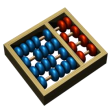




Figura 21: Carla Frame 407

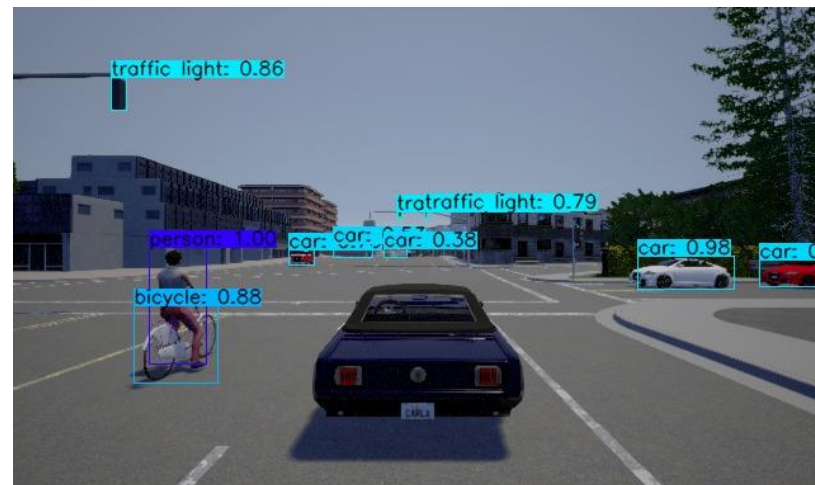


Figura 22: Carla Frame 407 + YOLO v3





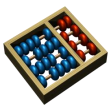
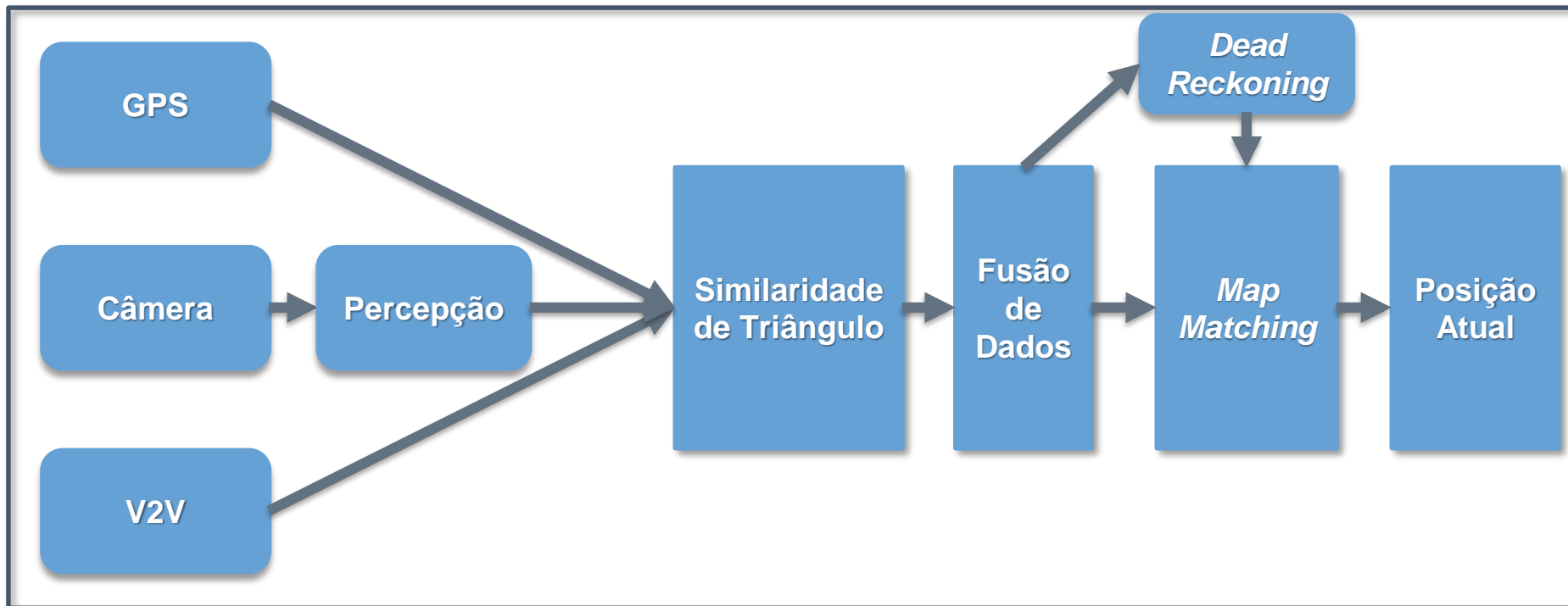


Figura 23: Carla Frame 518



Figura 24: Carla Frame 518 + YOLO v3



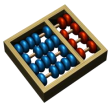
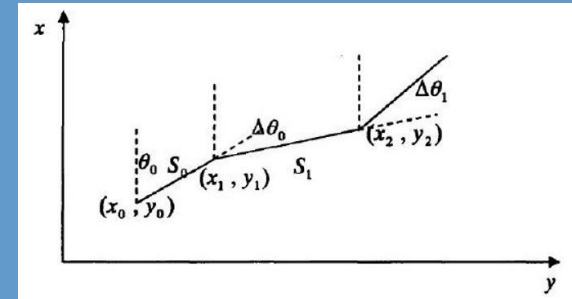


## Dead Reckoning

- 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.

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

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



- 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 ✔
- Avaliar os resultados de localização em novos cenários



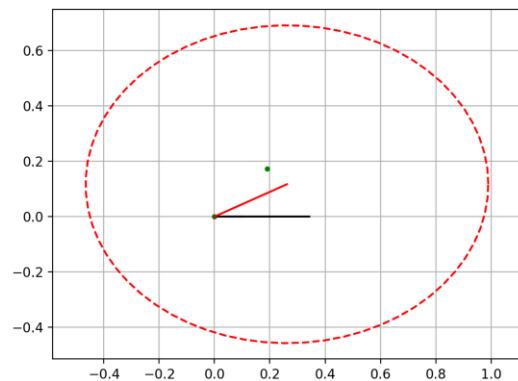


Figura 25: Extended Kalman  
Filter

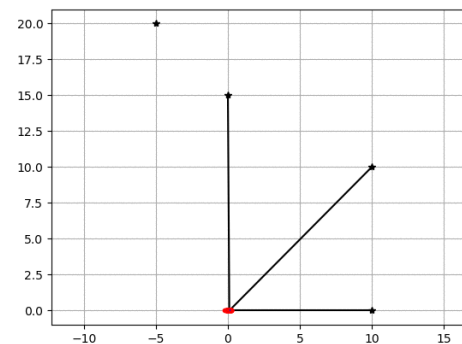


Figura 26: Particle Filter

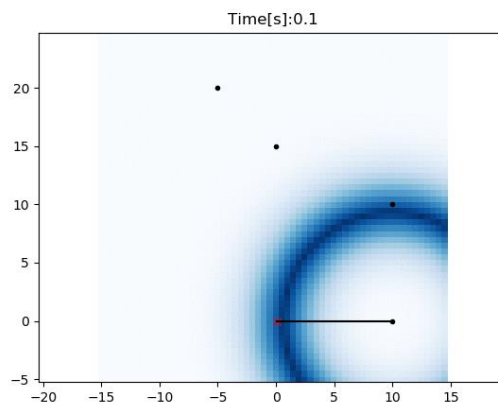


Figura 27: Histogram Filter



# Obrigado!



Dúvidas?



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