

Emprego de Sistemas de Visão na Agricultura

ZEB1066 – Tópicos Avançados em Engenharia de Biosistemas

Prof. Dr. Valdir Grassi Junior

vgrassi@usp.br

Introdução a visão computacional

Câmeras e Aquisição de Imagens

Câmera RGB



rehago.com.br

Especificar para sua aplicação:

- Campo de visão (distância focal da lente)
- Resolução da câmera (tamanho da imagem em pixels)

Câmeras e Aquisição de Imagens

Câmera Térmica



[FLIR](https://www.flir.com)



[Ray Asebedo](#)

Câmeras e Aquisição de Imagens

Câmera Multiespectral



[MicaSense](#)

RGB



Azul (475nm)

Verde (560nm)

Vermelho (717nm)



Vermelho (668nm)

Near IR (842nm)

Câmeras e Aquisição de Imagens

Câmera Multiespectral



[MicaSense](#)

Mapa de Clorofila



Azul (475nm)

Verde (560nm)

Vermelho (717nm)



Vermelho (668nm)

Near IR (842nm)

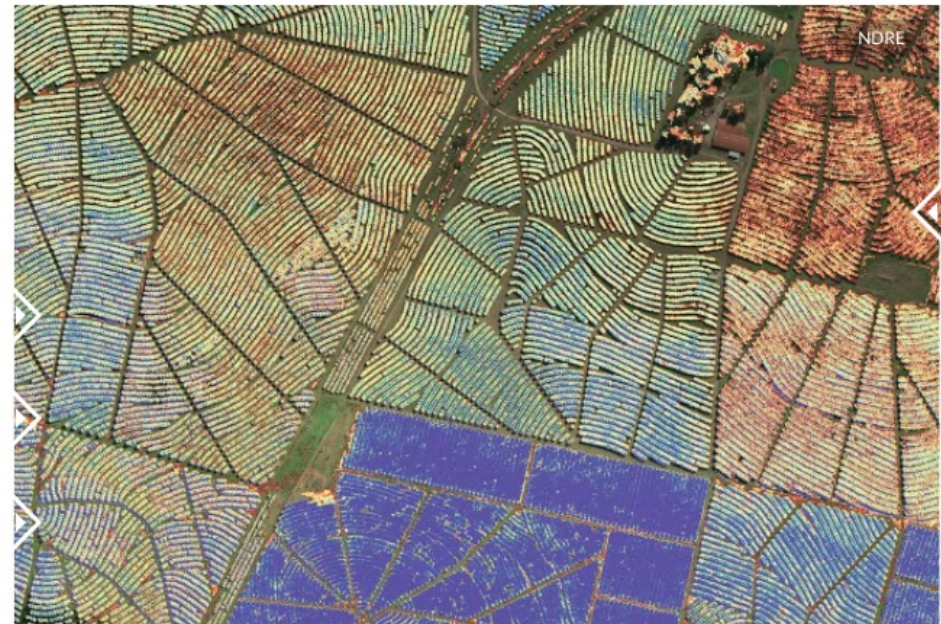
Câmeras e Aquisição de Imagens

Câmera Multiespectral



[MicaSense](#)

Normalized Difference Red Edge Index (NDRE)



Azul (475nm)

Verde (560nm)

Vermelho (717nm)



Vermelho (668nm)

Near IR (842nm)

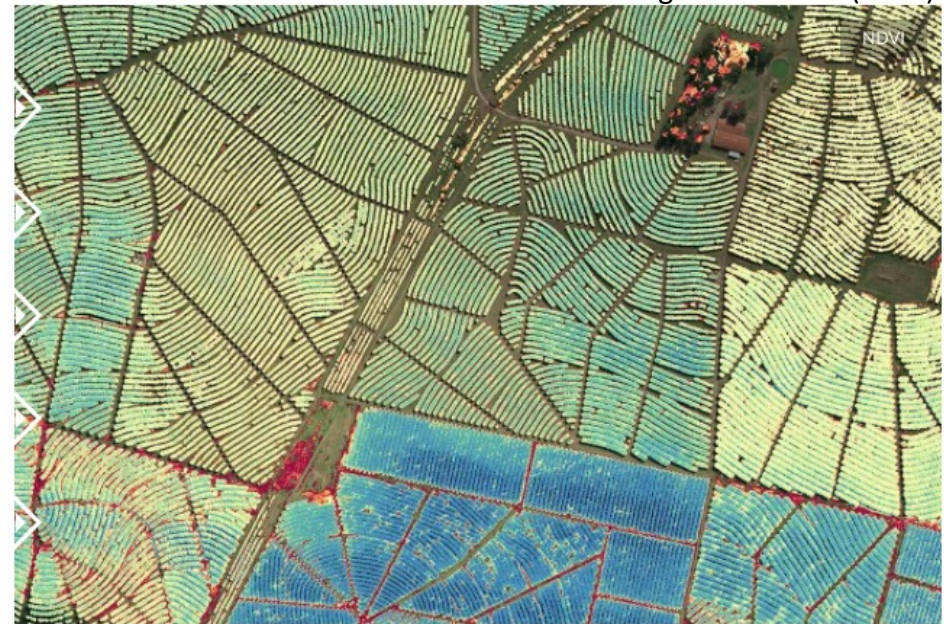
Câmeras e Aquisição de Imagens

Câmera Multiespectral



[MicaSense](#)

Normalized difference vegetation index (NDVI)



Azul (475nm)

Verde (560nm)

Vermelho (717nm)



Vermelho (668nm)

Near IR (842nm)

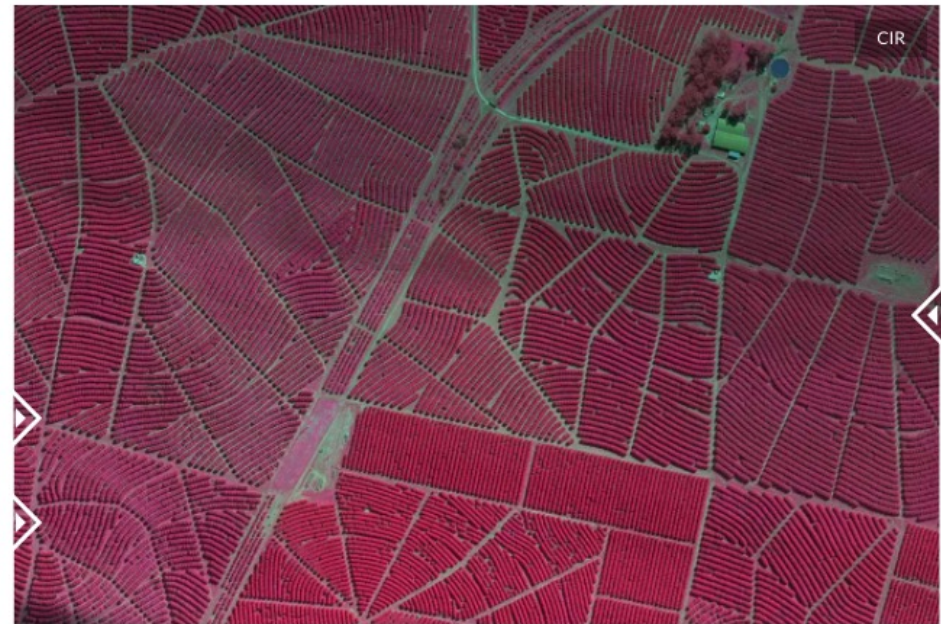
Câmeras e Aquisição de Imagens

Câmera Multiespectral



[MicaSense](#)

Color Infrared (CIR)



Azul (475nm)

Verde (560nm)

Vermelho (717nm)



Vermelho (668nm)

Near IR (842nm)

Imagens Digitais

- Níveis de cinza:
1 canal (matriz 2D)
Pixel com valores de 0 a 255



226	239	237	237	236	233	236	238	232	229	229	227	228	231	238	244	237	226	225
230	245	212	191	190	201	225	225	222	222	224	221	224	237	232	217	204	201	220
234	255	223	159	117	151	201	207	210	217	223	220	223	233	194	137	123	152	202
238	250	230	131	71	121	176	198	207	217	221	218	213	187	102	47	88	166	214
232	237	223	153	95	84	125	184	206	219	224	213	165	90	31	58	141	207	224
215	218	222	198	135	78	94	151	184	197	202	164	86	39	70	148	195	205	205
204	204	207	196	139	112	114	122	152	164	164	101	31	51	143	211	218	208	200
204	196	198	195	163	157	159	127	112	102	79	48	55	115	188	224	219	211	203
198	191	189	193	193	198	207	149	72	31	0	31	121	188	211	214	211	209	204
193	191	190	194	202	211	219	159	56	1	1	69	161	200	208	211	214	217	208
197	197	197	206	221	219	180	101	30	22	61	103	127	164	200	208	217	221	209
197	202	204	209	207	167	95	48	63	111	152	139	111	128	148	177	211	212	205
193	204	208	205	165	84	28	60	139	198	210	175	159	128	79	135	196	196	200
191	207	215	181	105	45	49	111	174	207	215	196	191	154	93	111	153	174	192
192	206	192	124	51	52	121	176	188	191	200	205	206	187	146	95	92	143	178
194	200	169	84	50	108	175	201	197	196	199	201	201	194	168	102	86	142	173
190	192	177	129	131	185	207	207	203	201	198	196	193	191	176	141	139	172	180
186	190	188	182	203	221	210	202	202	201	196	193	190	186	179	173	176	186	187
183	187	193	188	189	198	195	191	191	194	195	191	188	184	183	184	185	185	184

Imagens Digitais

- RGB
3 canais (R,G,B)
pixel com valores de 0 a 255

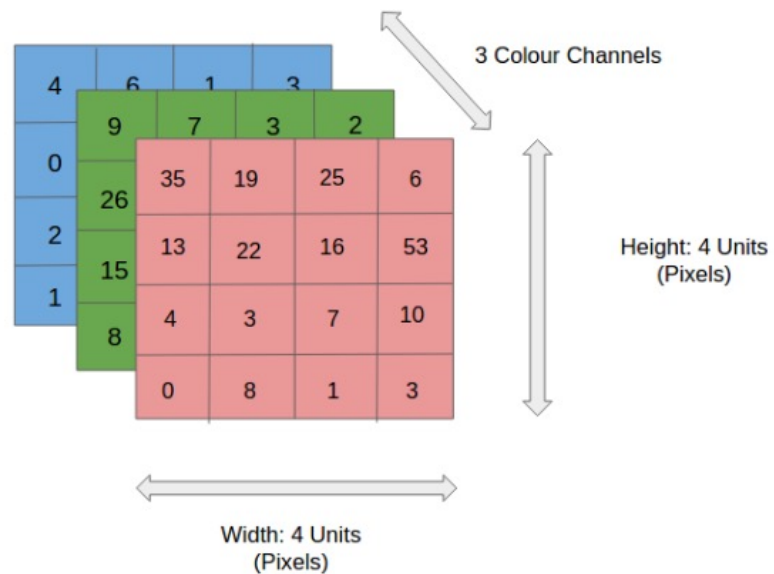
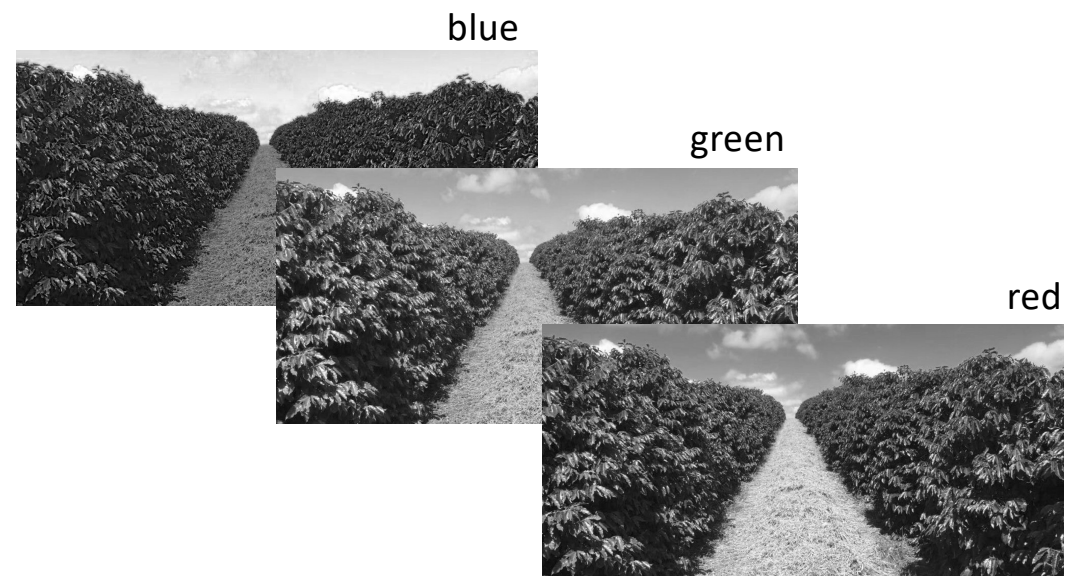


Imagem: [Saha, S. \(2018\)](#)



Imagem

- Níveis de cinza
1 canal
pixel com valores de 0 a 255

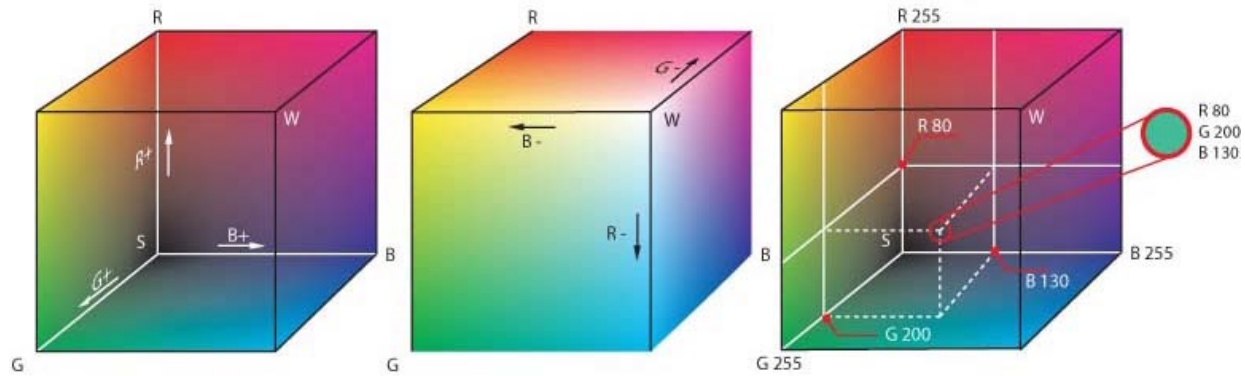


- RGB
3 canais (R,G,B)
pixel com valores de 0 a 255

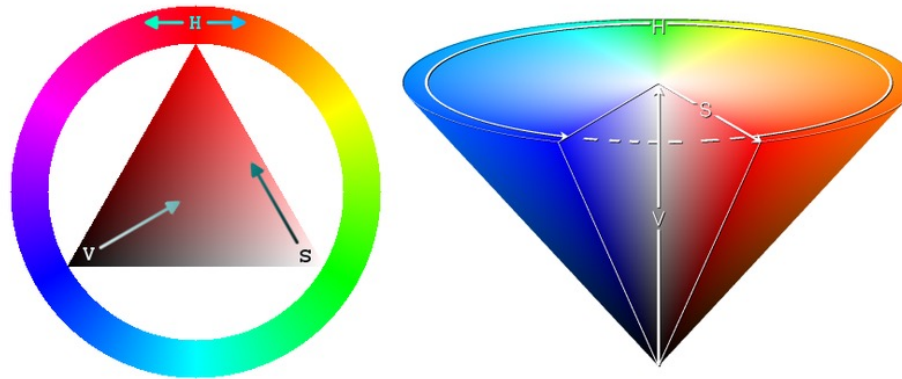


Espaço de Cores

- RGB



- HSV ou HSI

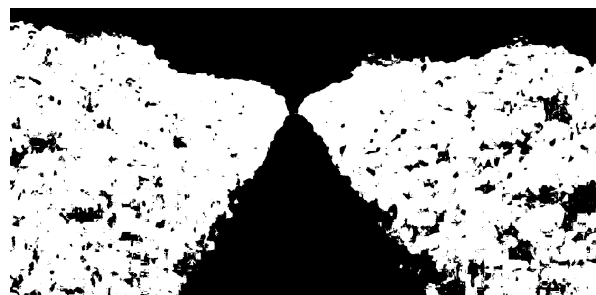


Imagens Digitais

- HSV
3 canais (H,S,V)
pixel com valores de 0 a 255



$10 < H < 30$

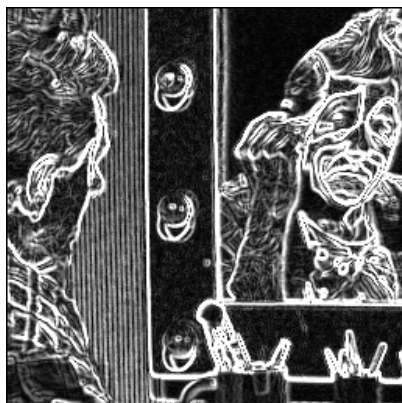


$32 < H < 90$

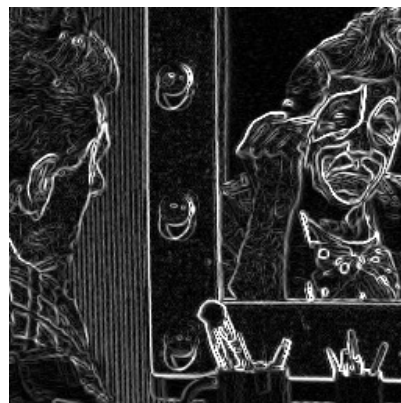


$95 < H < 115$

Detecção de Bordas



Resultado do Sobel



Resultado do Roberts

Detecção de Bordas



Resultado do Sobel

Convolução

1	0	1
0	1	0
1	0	1

Máscara ou Filtro

1 _{x1}	1 _{x0}	1 _{x1}	0	0
0 _{x0}	1 _{x1}	1 _{x0}	1	0
0 _{x1}	0 _{x0}	1 _{x1}	1	1
0	0	1	1	0
0	1	1	0	0

Imagem

4		

Resultado da Convolução

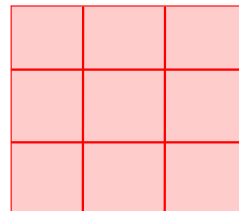
Convolução

Filtro Sobel:

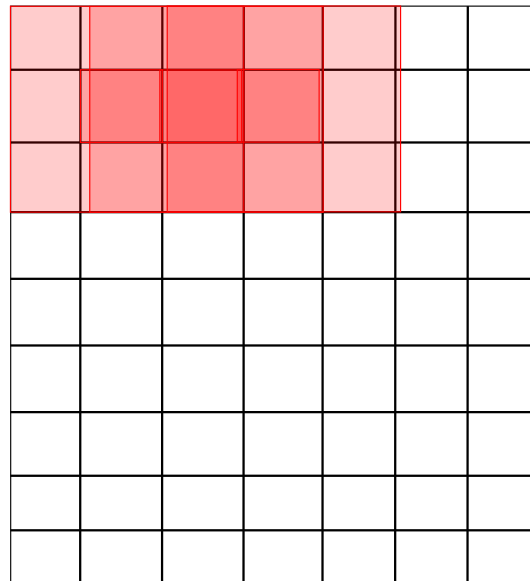
$$G_x : \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}$$

$$G_y : \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix}$$

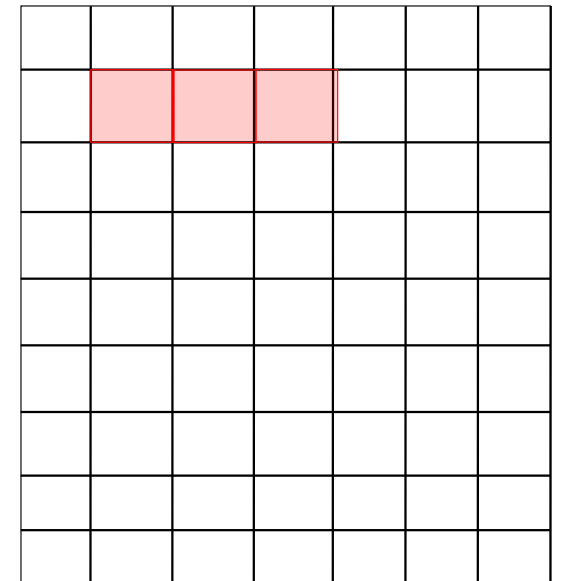
A



I



I_A



Detecção de Retas e Círculos

Hough Transform - Lines

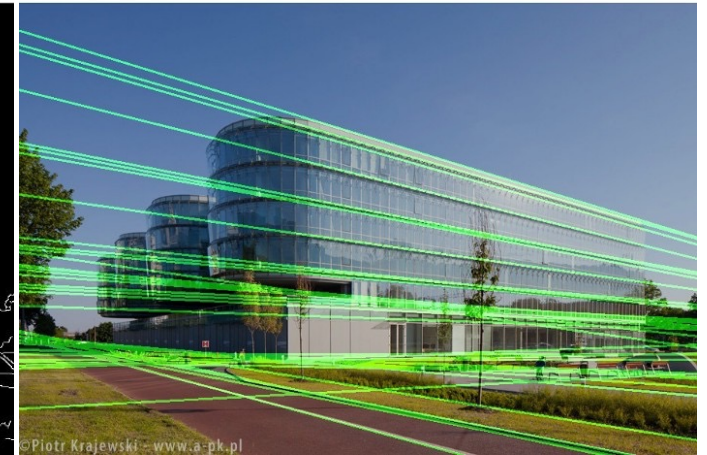
Original image



Edge image

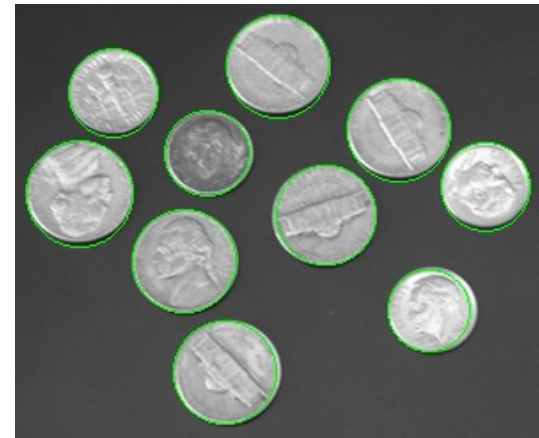
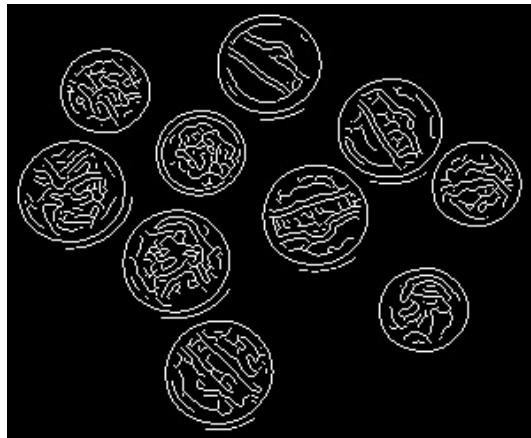


Image with Hough Lines



Detecção de Retas e Círculos

Hough Transform - Circles

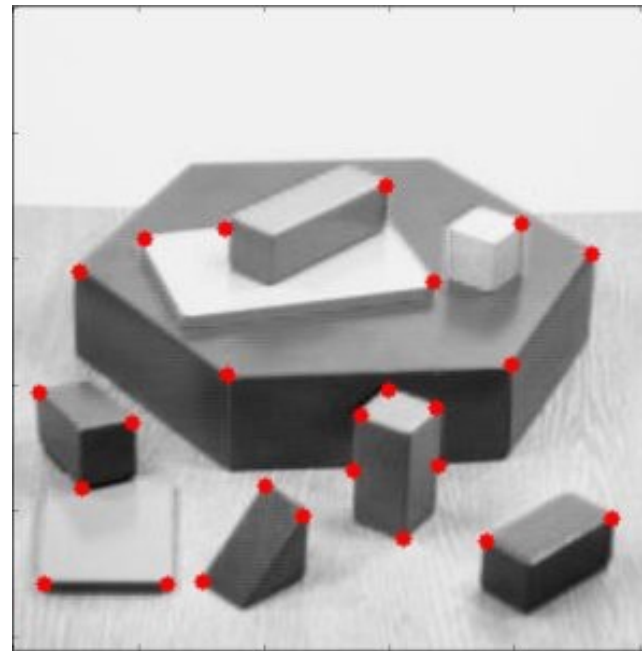


Detecção de Cantos

Método de Harris para Detecção de Cantos



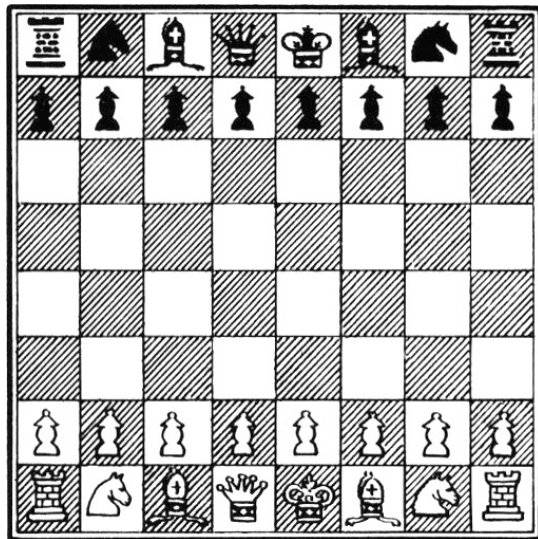
<https://summervisionproject.com/harris-corner-detection/>



medium.com

Detecção de Cantos

Método de Harris para Detecção de Cantos



Extração de Características (*Features*)

SIFT – Scale Invariant Feature Transform

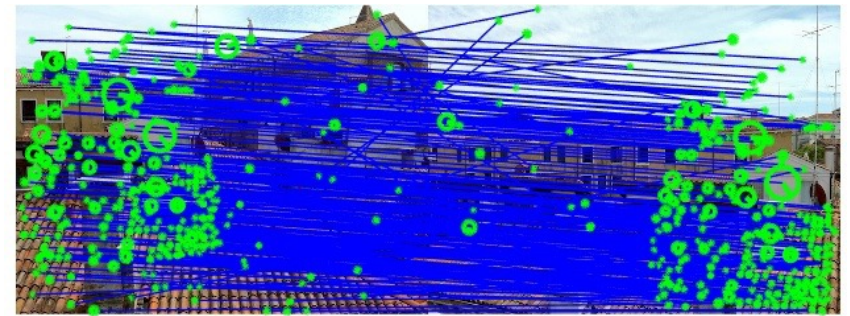


[VLFeat](#)

David G. Lowe, "Distinctive image features from scale-invariant keypoints," *International Journal of Computer Vision*, 60, 2 (2004), pp. 91-110

Extração de Características (*Features*)

SIFT – Scale Invariant Feature Transform



Matching (Correspondência)

Extração de Características (*Features*)

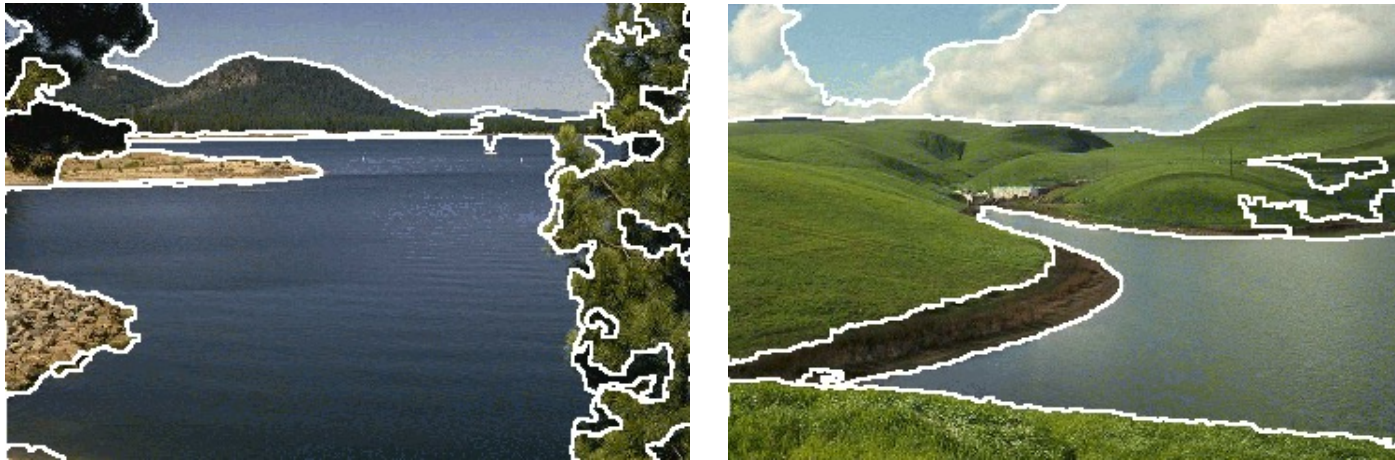
- SIFT – Scale Invariant Feature Transform (2004)
- SURF – Speeded Up Robust Features (2006)
- FAST – Speeded Up Robust Features (2006)
- BRIEF – Binary Robust Independent Elementary Features (2010)
- ORB – an efficient alternative to SIFT or SURF (2010)
- LIFT - Learned Invariant Feature Transform (2016)
- SuperPoint (2017)
- LF-NET (2018)
- D2-NET (2019)
- R2D2 (2019)

Correspondência por Correlação



Segmentação de Imagens

Mean Shift



Comaniciu, D.; Meer, P.; *Mean Shift: A Robust Approach Toward Feature Space Analysis*. IEEE Trans. on Pattern Analysis and Machine Intelligence, vol 24, no. 5, 2002.

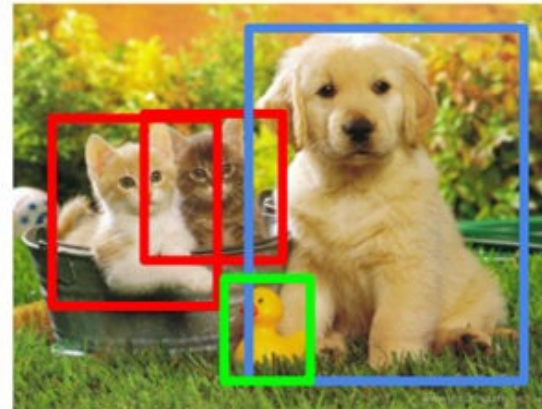
Classificação e Detecção de Objetos

Classification



CAT

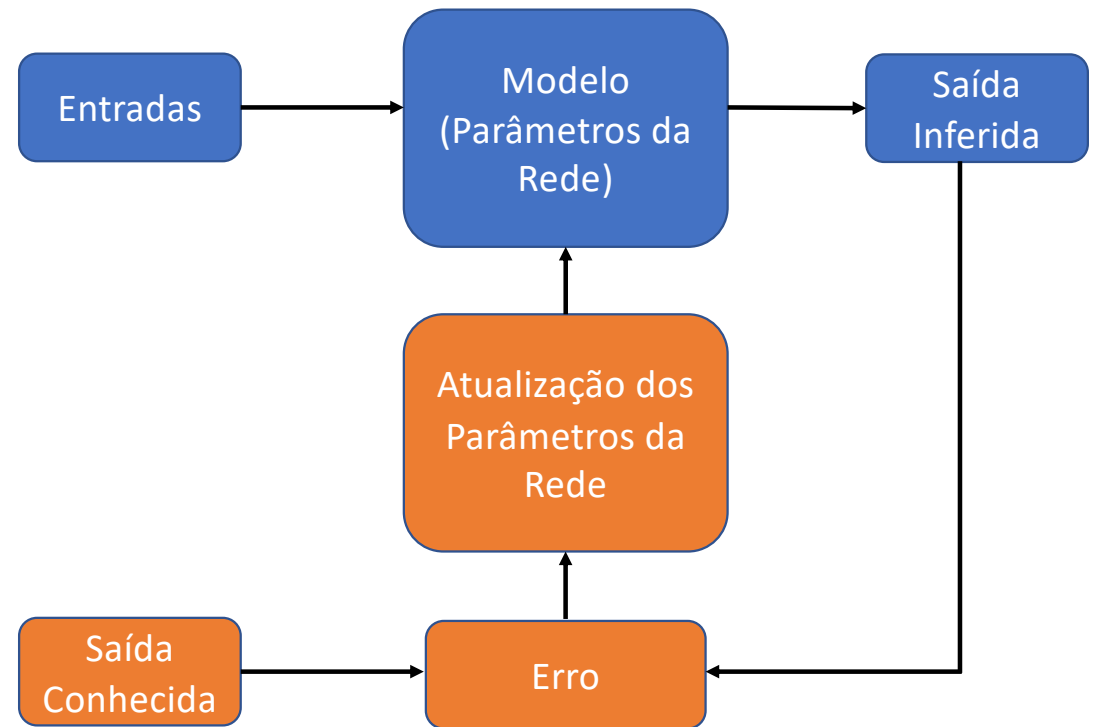
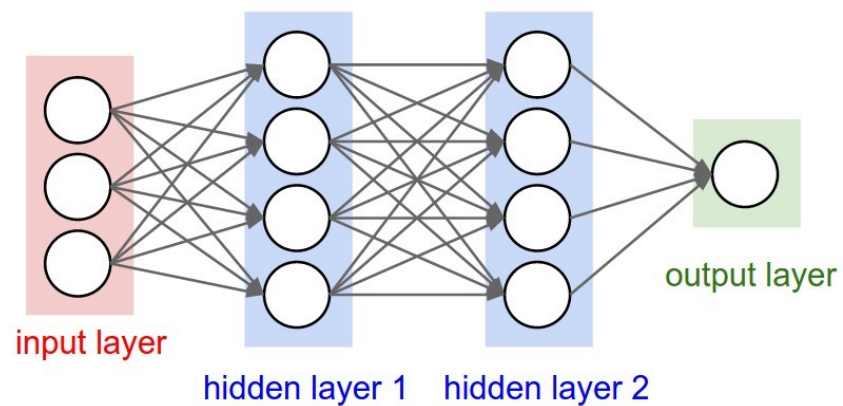
Object Detection



CAT, DOG, DUCK

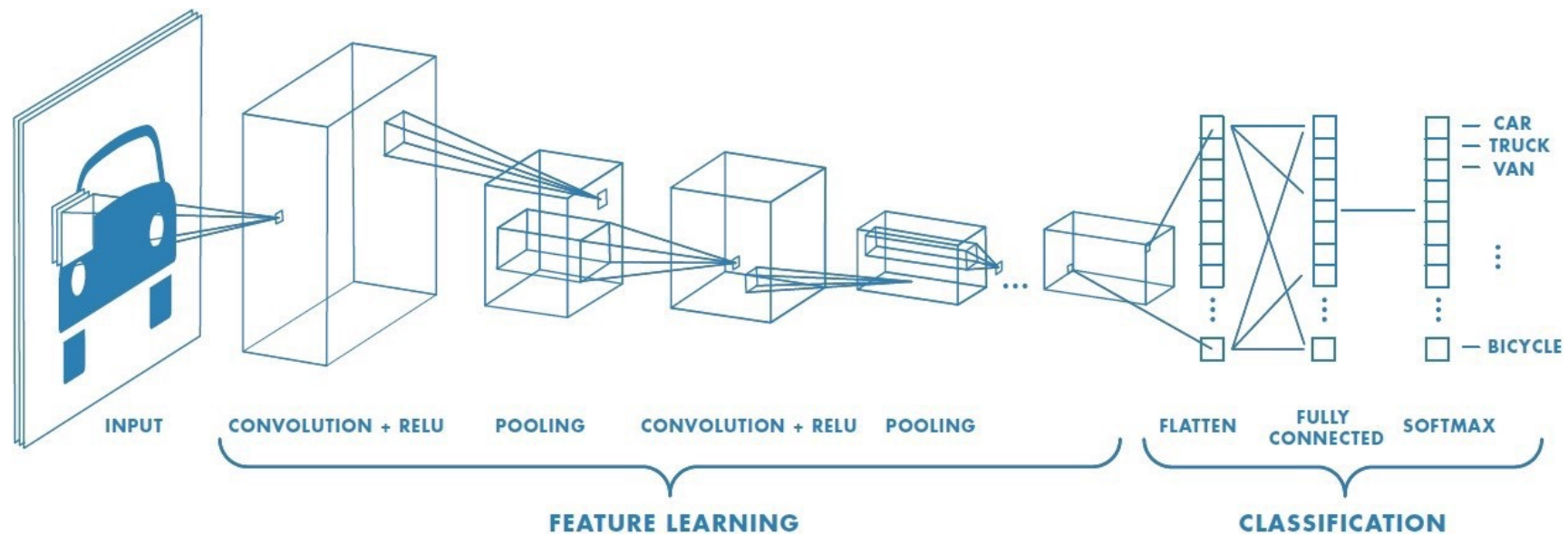
<https://www.datacamp.com/community/tutorials/object-detection-guide>

Aprendizado de Máquinas



Aprendizado Profundo

- Redes Neurais Convolucionais



Segmentação (SegNet)

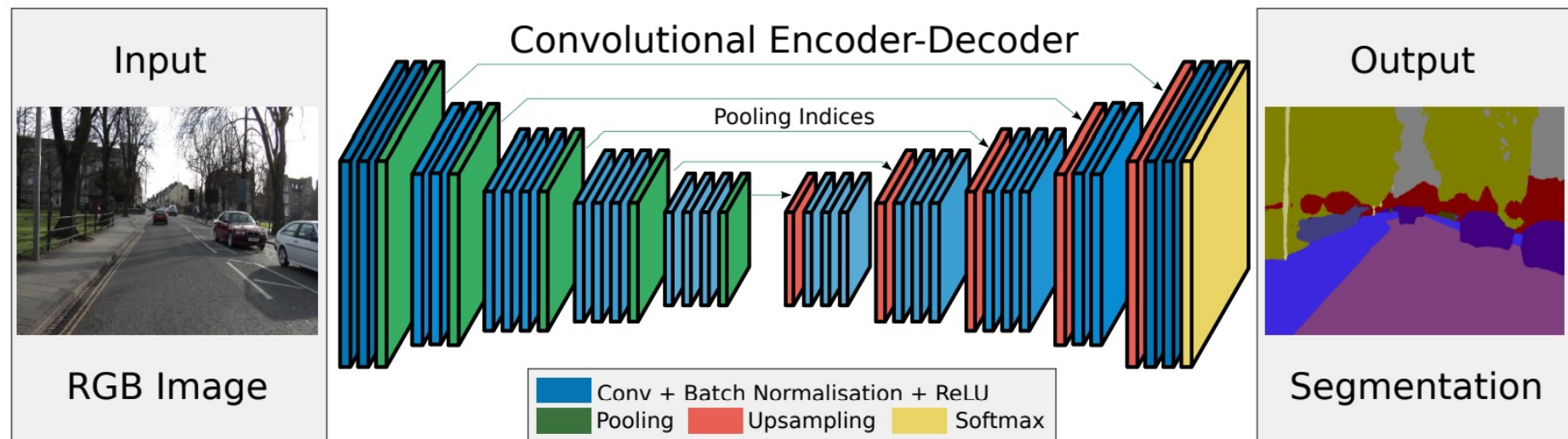
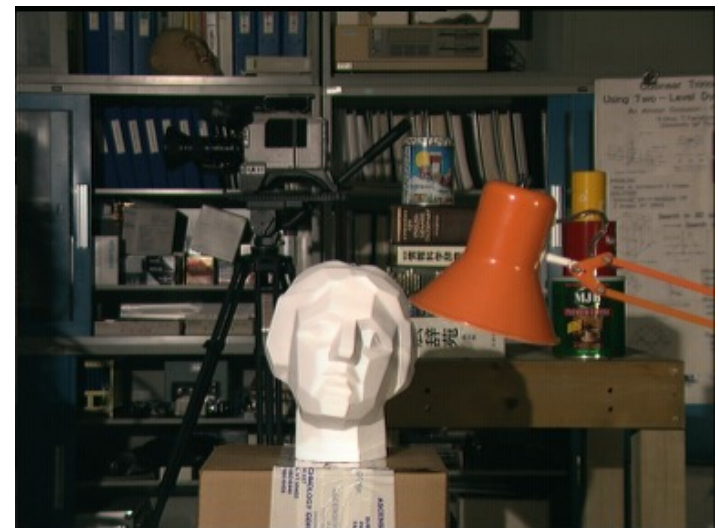
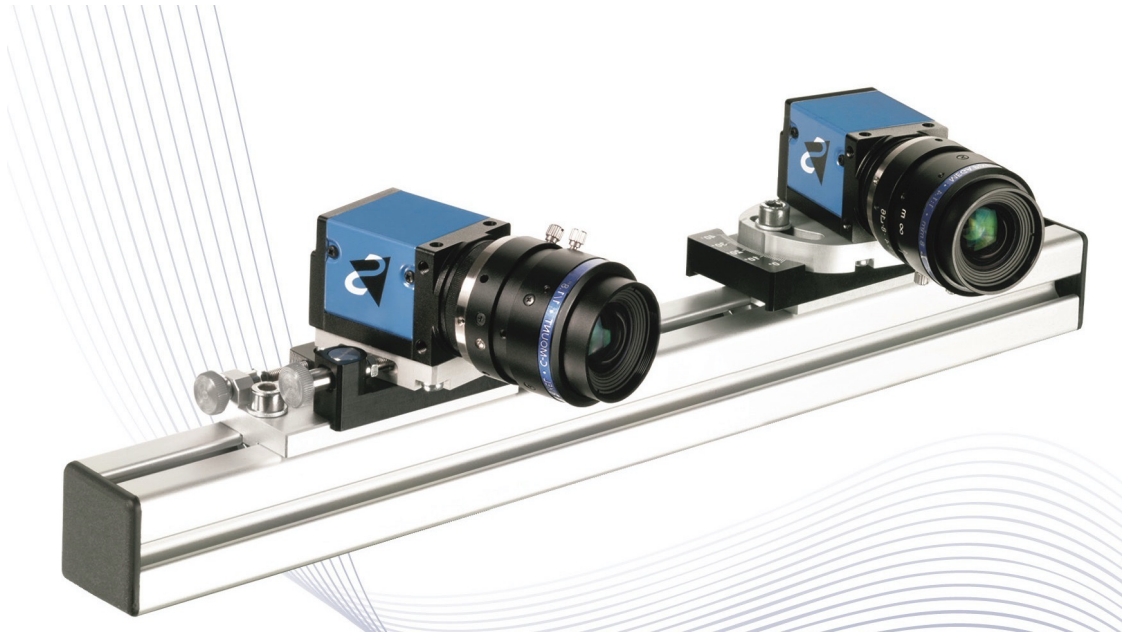
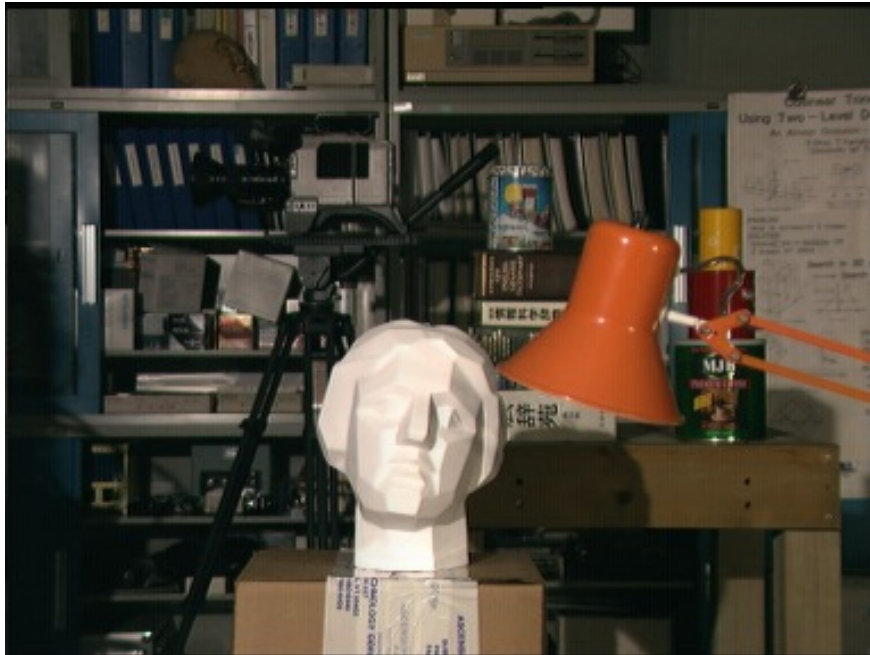


Fig. 2. An illustration of the SegNet architecture. There are no fully connected layers and hence it is only convolutional. A decoder upsamples its input using the transferred pool indices from its encoder to produce a sparse feature map(s). It then performs convolution with a trainable filter bank to densify the feature map. The final decoder output feature maps are fed to a soft-max classifier for pixel-wise classification.

Visão Estéreo

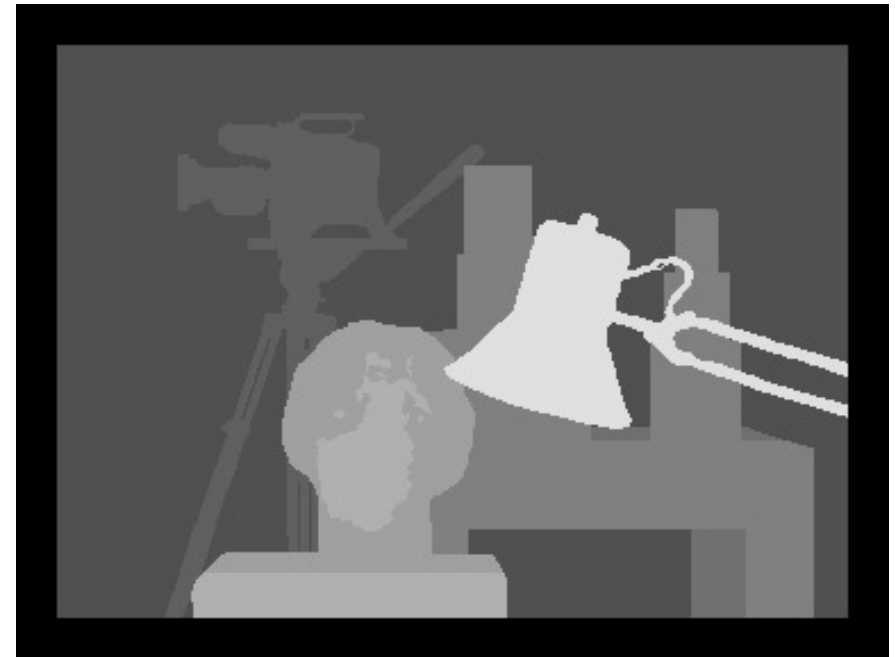


Visão Estéreo



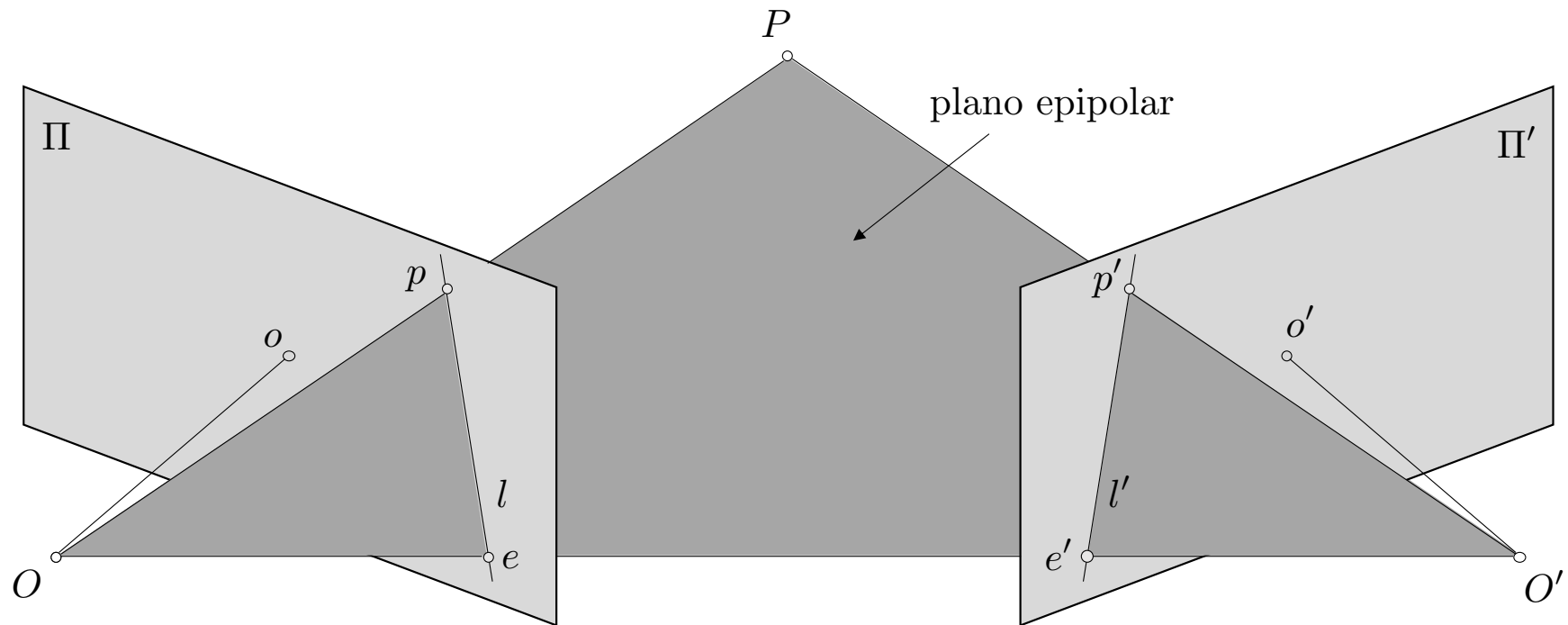
Tsukuba Dataset

Visão Estéreo



Mapa de Disparidade

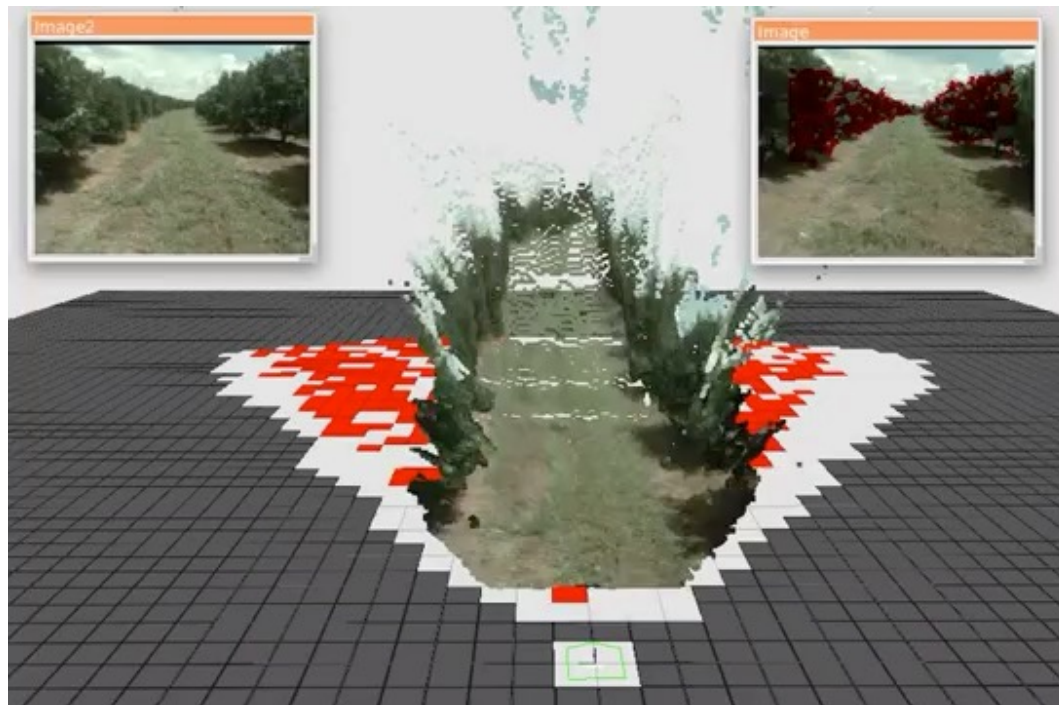
Visão Estéreo



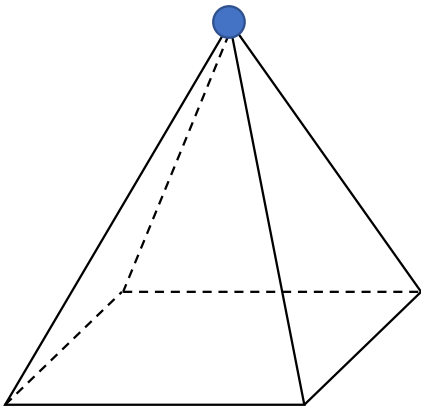
Visão Estéreo



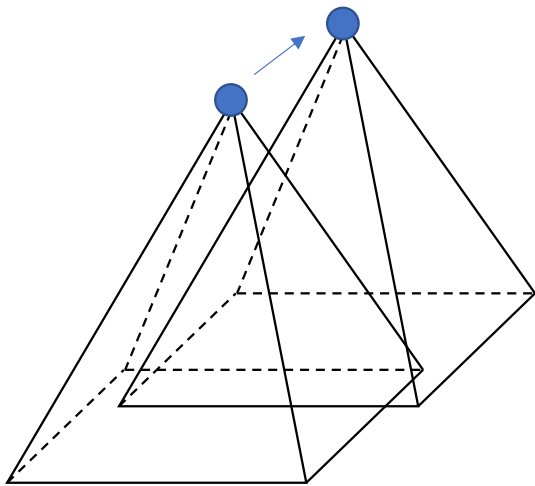
Visão Estéreo



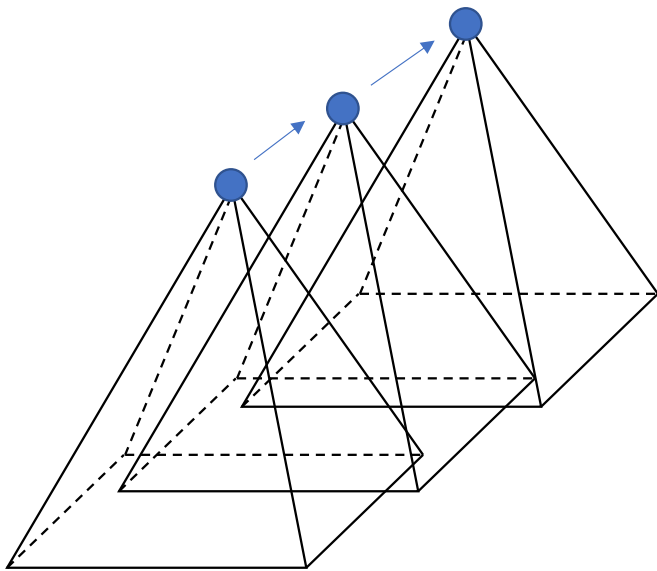
Mosaico de Imagens



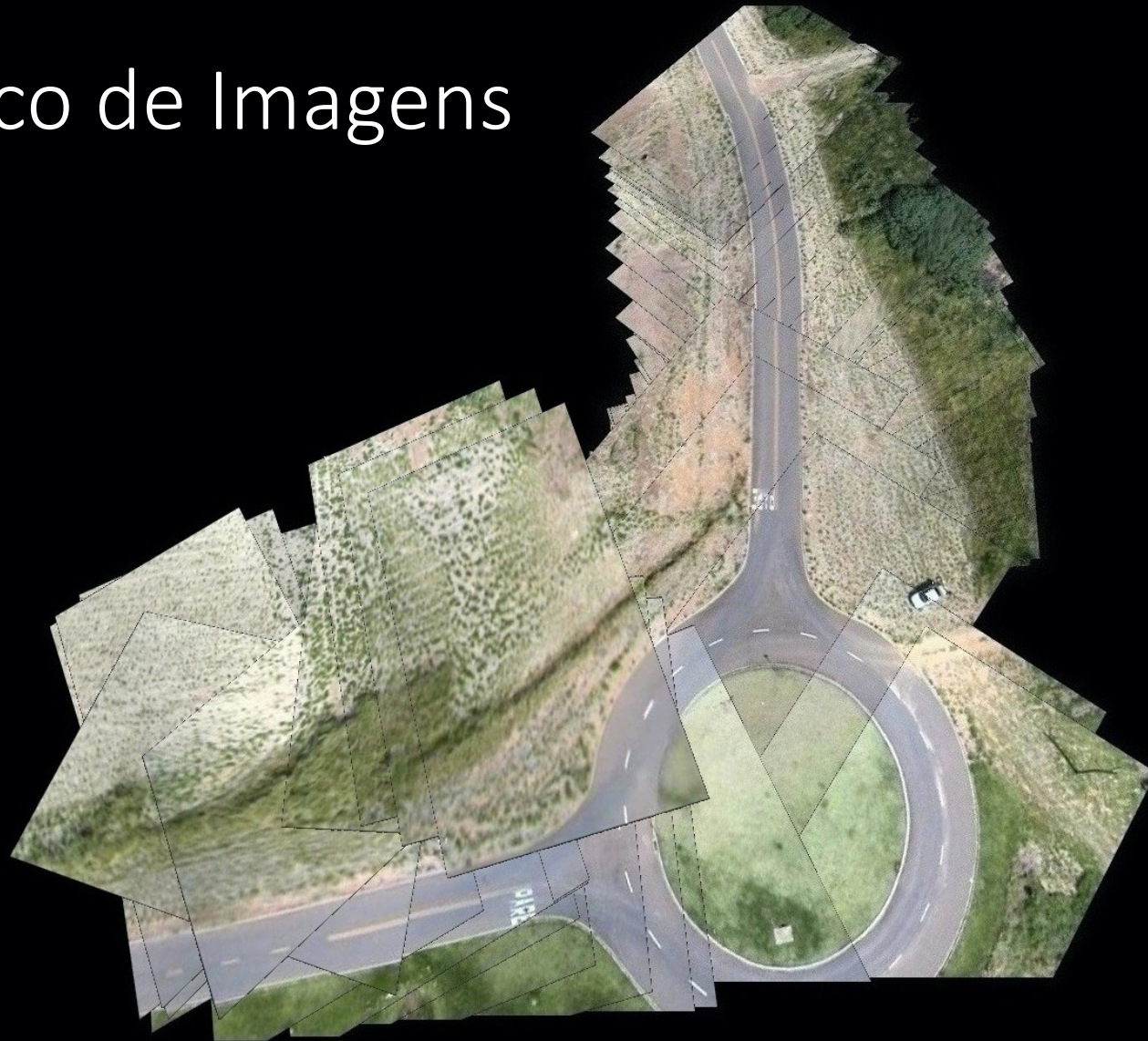
Mosaico de Imagens



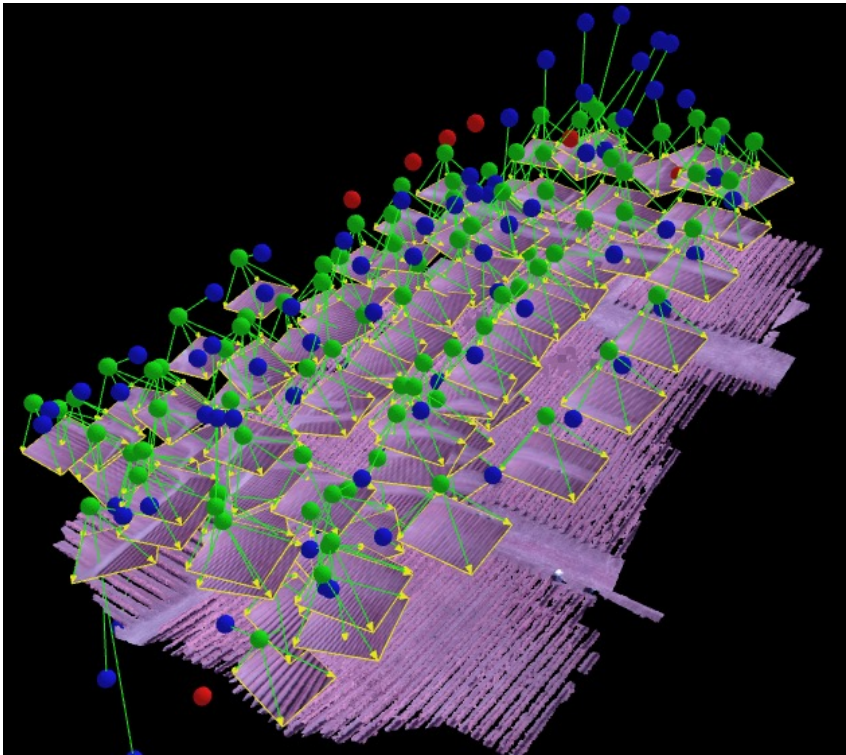
Mosaico de Imagens



Mosaico de Imagens



Mosaico de Imagens



<https://diydrones.com/profiles/blogs/great-post-on-agricultural-drone-mapping>



Aplicações na agricultura



Universidade de São Paulo
Brasil

Inscrição SIICUSP: 3931

Deteccção de plantas utilizando algoritmos de segmentação e de constância de cor para navegação robótica

Autor: Gabriel Corrêa de Oliveira

Orientador: Marcelo Becker



29º SIICUSP - 2021



EESC • USP



Problema de pesquisa



Navegação autônoma do TerraSentia

Folhas obstruindo o caminho



Método

Pré-processamento

Segmentação

Classificação

Remoção

Filtro e espaço de cor

Superpixel

Descritores e machine learning

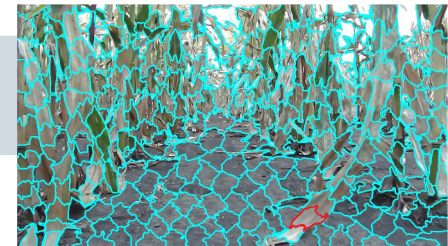
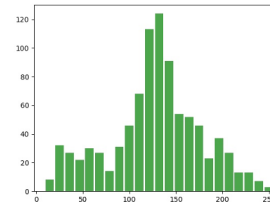
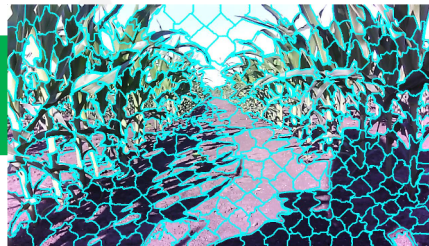
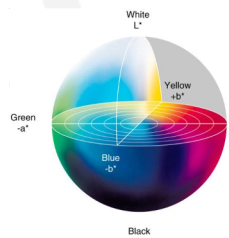
Detecção folhas obstrutoras

Filtro gaussiano e índice de cor

Fast-SLIC

Folha, solo e céu

Busca por *superpixels* fora da região usual





Teste da eficácia do método da odometria visual no robô TerraSentia

Jorge Id Facuri Filho
Vitor Akihiro Hisano Higuti
Marcelo Becker

USP - EESC - SEM
Mechanical Engineering Department
LabRoM - Mobile Robotics Lab.

jorgeid@usp.br



Odometria Visual

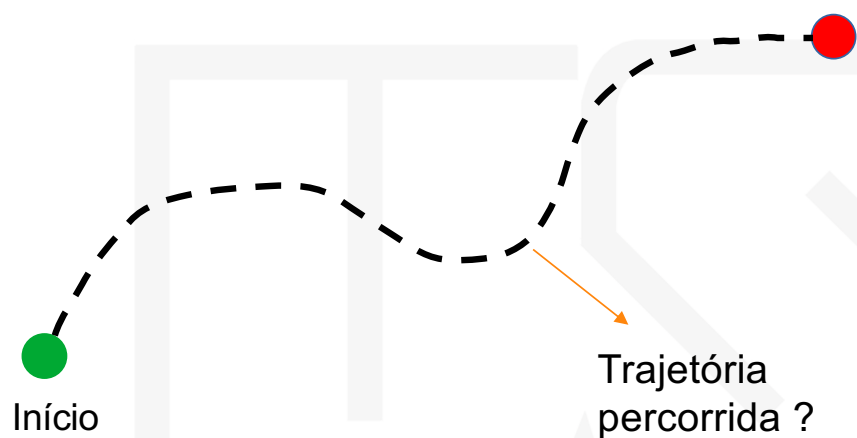


Figura 1. Trilha de um Milharal. Fonte: Veja, 2017



Nº 2924

NAVEGAÇÃO AUTÔNOMA POR DENTRO DE PLANTAÇÕES UTILIZANDO VISÃO COMPUTACIONAL

Gabriel Lima Araujo
Prof. Marcelo Becker

USP - EESC - SEM
Mechanical Engineering Department
LabRoM - Mobile Robotics Lab.



Conduzir o robô de pequeno porte (TerraSentia) por dentro dos corredores da plantação de milho utilizando visão computacional.



Plantação de milho utilizada na pesquisa

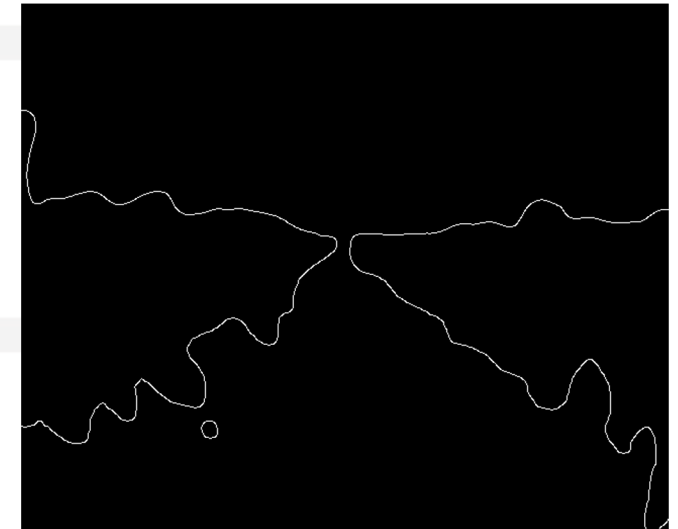
Método Aplicado



Filtro gauss aplicado

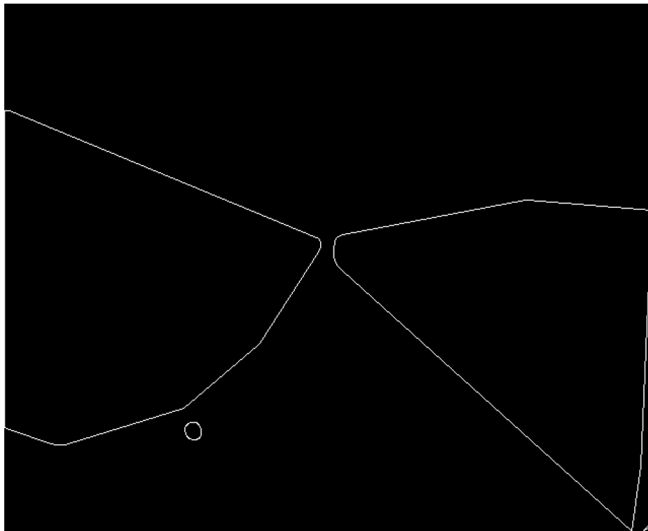


Binarização e operação de abertura aplicadas

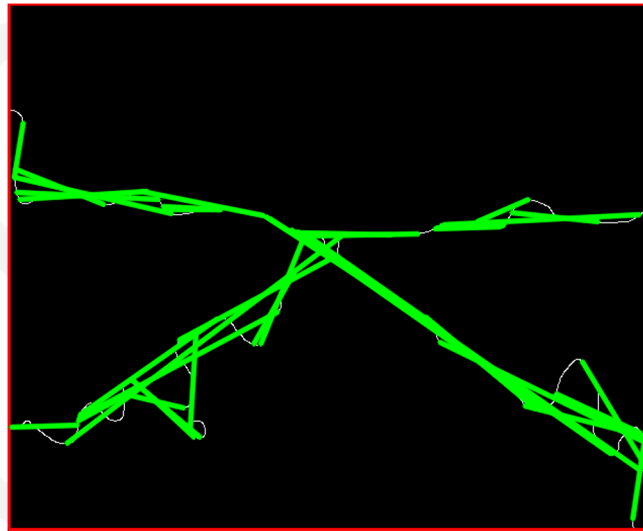


Deteção de borda (Canny) aplicada

Método Aplicado



Operação de invólucro convexo



Transformada Hough aplicada



Definição da direção

Resultados



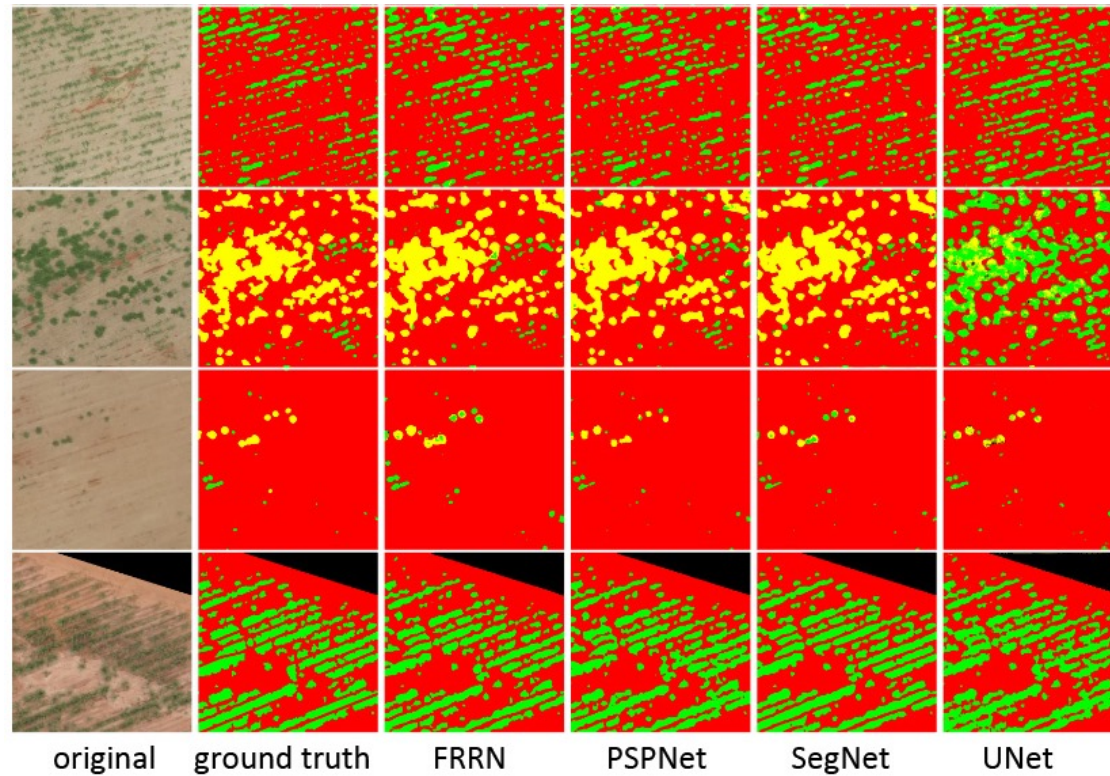
Direção definida pelo método em verde e resultado esperado em vermelho.



Direção definida pelo método em verde e resultado esperado em vermelho.

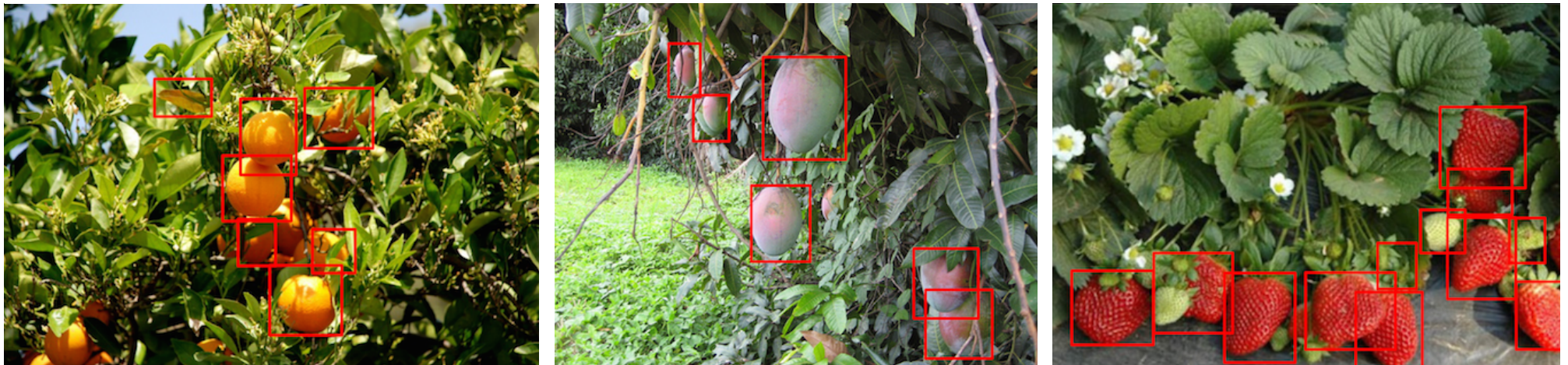
Aplicações de Deep Learning

Detecção de Ervas Daninhas



<https://github.com/awangenh/Weed-Mapping>

Detecção de Frutas



Sa, I.; Ge, Z.; Dayoub, F.; Upcroft, B.; Perez, T.; McCool, C. DeepFruits: A Fruit Detection System Using Deep Neural Networks. *Sensors* **2016**, *16*, 1222. <https://doi.org/10.3390/s16081222>

Estimativa Monocular de Profundidade

- Aprendizado profundo supervisionado para estimativa monocular de profundidade;
- Arquitetura proposta: DenseSIDENet;
- Parâmetros de treinamento: 2M até 12M;
- Predição entre 32fps a 88fps;
- Capaz de estimar profundidade e normal de superfícies;



Imagem de câmera embarcada no veículo

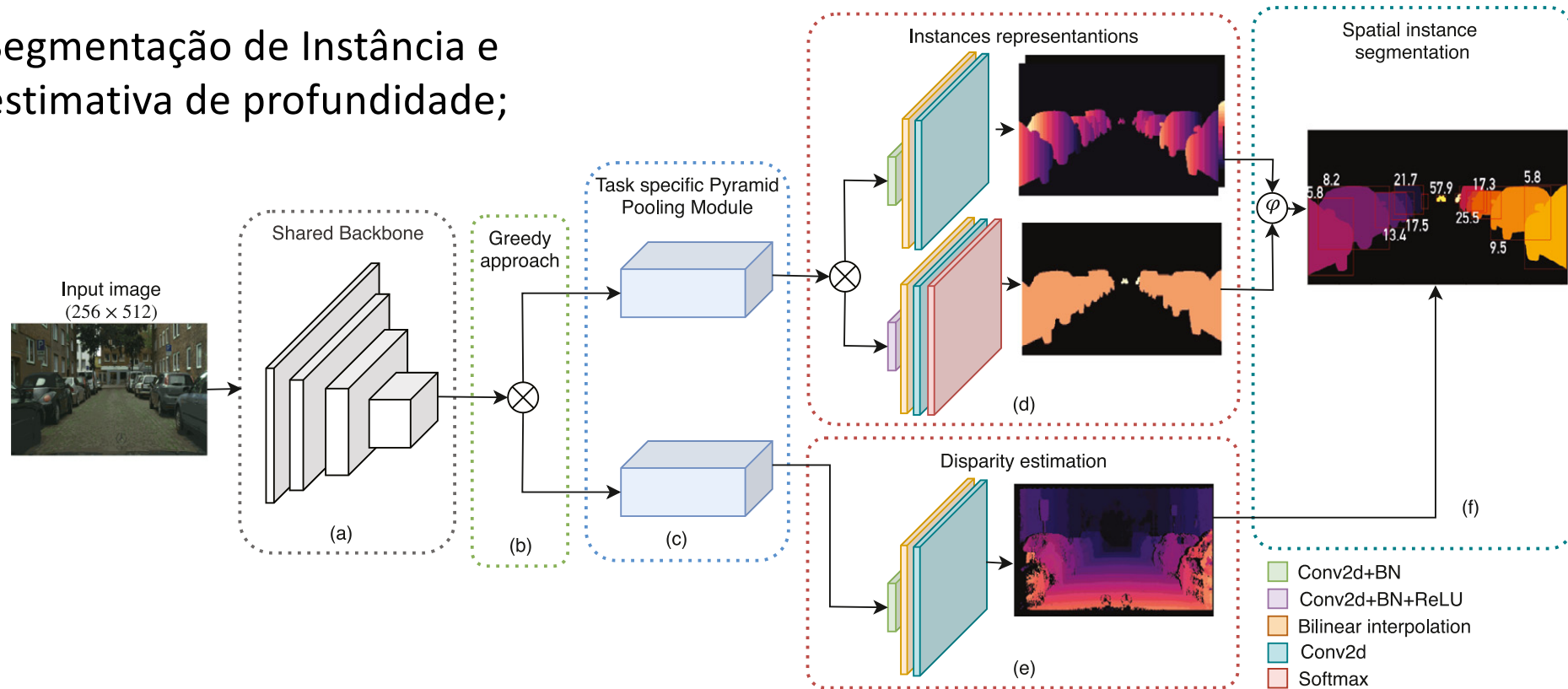


*Resultado de estimativa de profundidade.
Cores quentes indicam objetos mais próximos da câmera.*

MENDES, R. d. Q.; RIBEIRO, E. G.; ROSA, N. S.; GRASSI JR., V. On deep learning techniques to boost monocular depth estimation for autonomous navigation. **Robotics and Autonomous Systems**, v. 136, p. 103701, 2021

Aprendizado Simultâneo de Múltiplas Tarefas

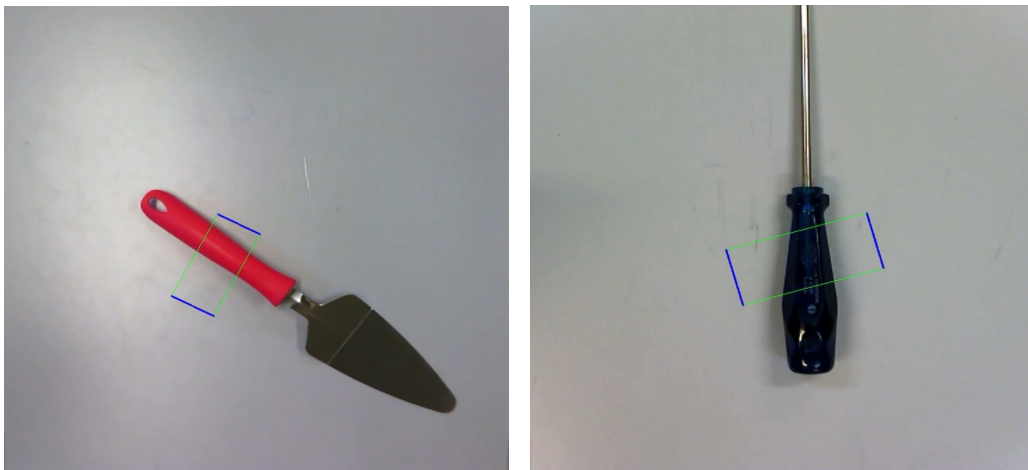
Segmentação de Instância e estimativa de profundidade;



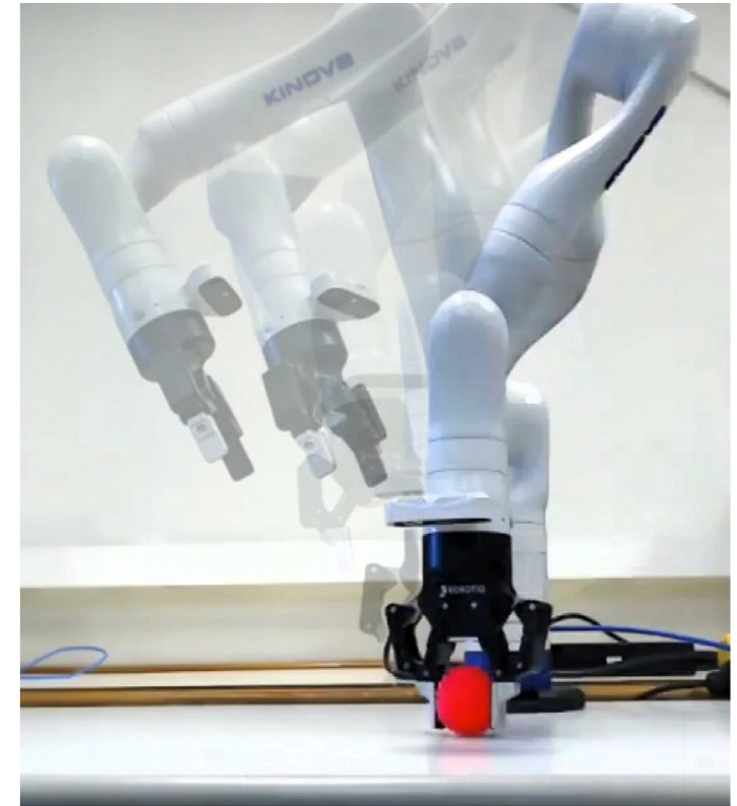
NAKAMURA, A. T. M.; GRASSI JR., V.; WOLF, D. F. An effective combination of loss gradients for multi-task learning applied on instance segmentation and depth estimation. **Engineering Applications of Artificial Intelligence**, v. 100, p. 104205, 2021.

Manipulação Robótica

- Rede neural convolucional para detecção de pontos de preensão robótica.



Pontos de preensão detectados em azul

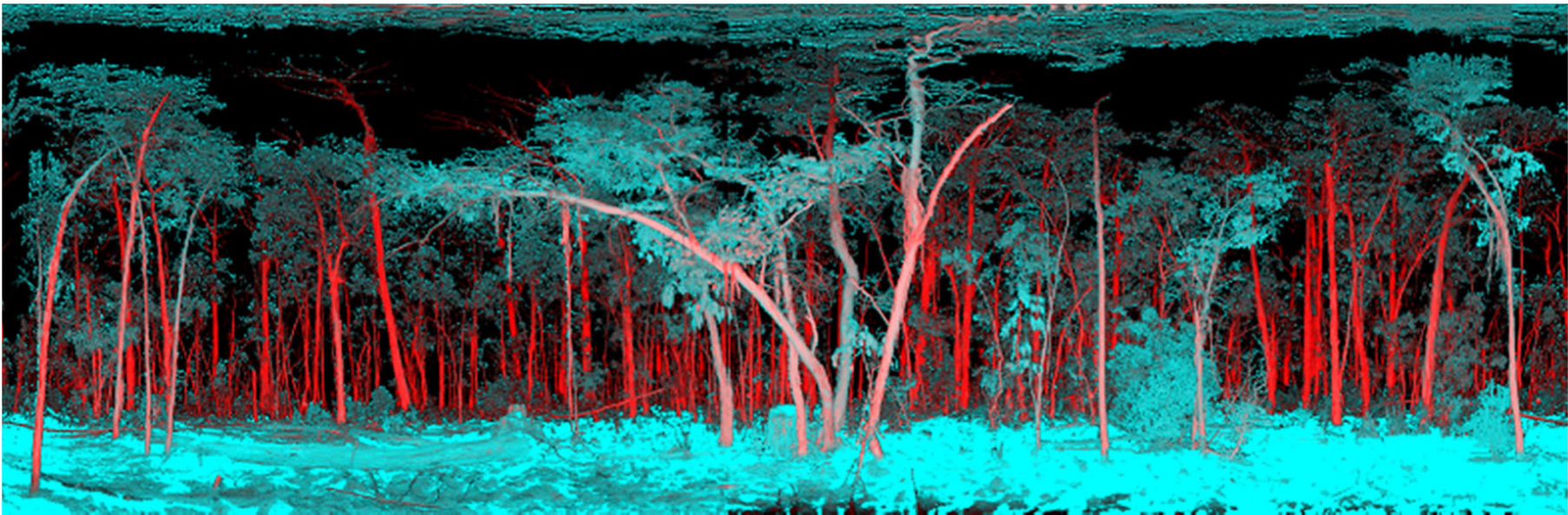


RIBEIRO, E. G.; MENDES, R. d. Q.; GRASSI JR., V. Real-time deep learning approach to visual servo control and grasp detection for autonomous robotic manipulation. **Robotics and Autonomous Systems**, v. 139, p. 103757, 2021.

LiDAR



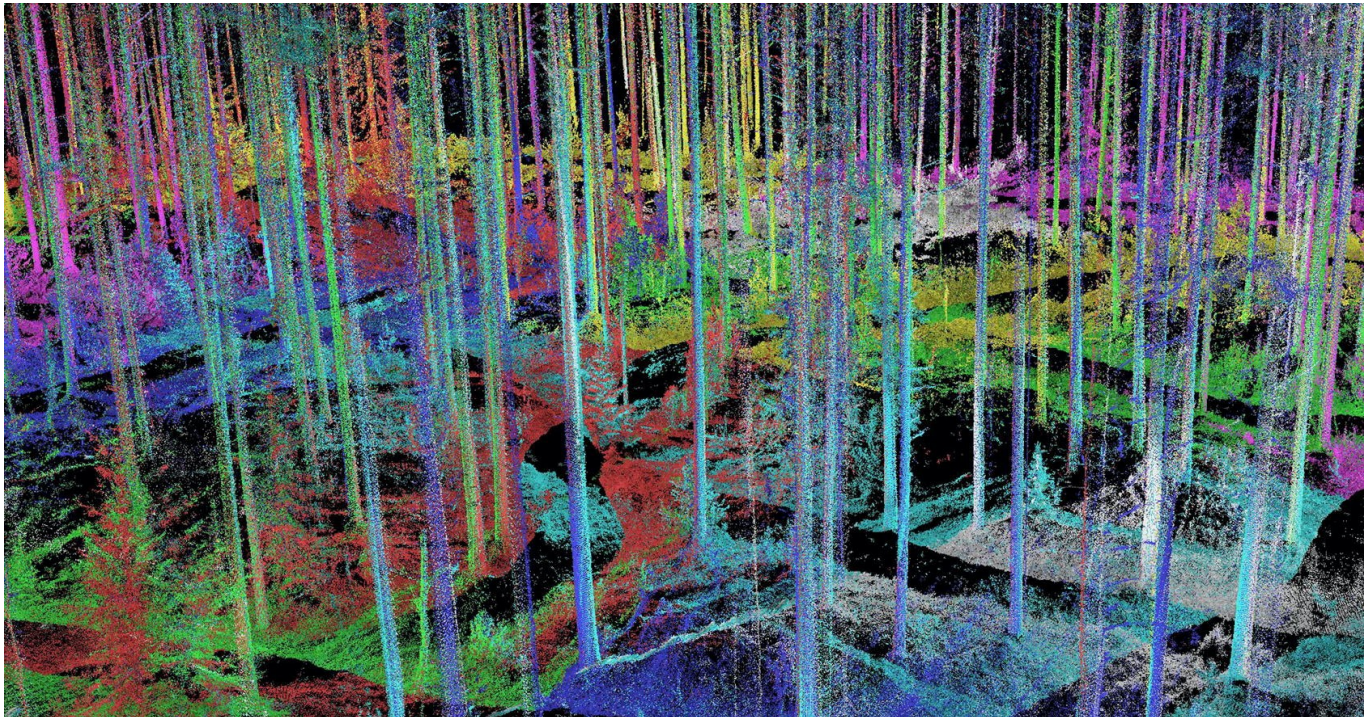
Mapeamento de Florestas



Dual-wavelength Echidna LiDAR (DWEL)

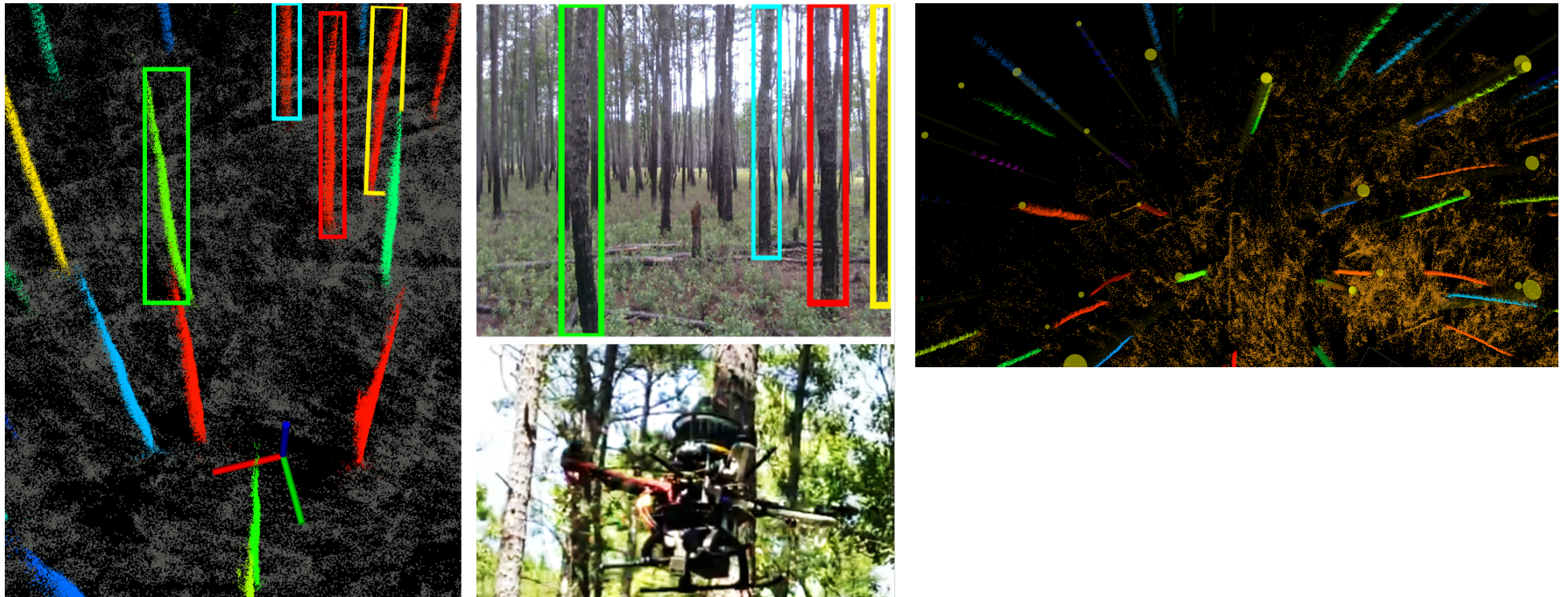
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Obrigado!