

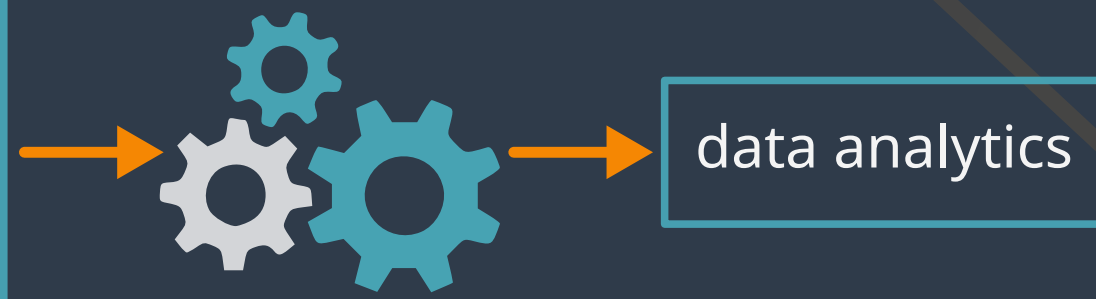
Vehicle Semantics Extraction and Retrieval for Long-term Carpark Video Surveillance

Clarence Cheong¹, Ryan Lim¹, John See¹, Lai-Kuan Wong¹, Ian K.T. Tan¹ and Azrin Aris²
¹Center for Visual Computing, Multimedia University, Persiaran Multimedia, 63100 Cyberjaya, Malaysia
²VADS Lyfe, Telekom Malaysia Berhad, 60000 Kuala Lumpur, Malaysia

Abstract

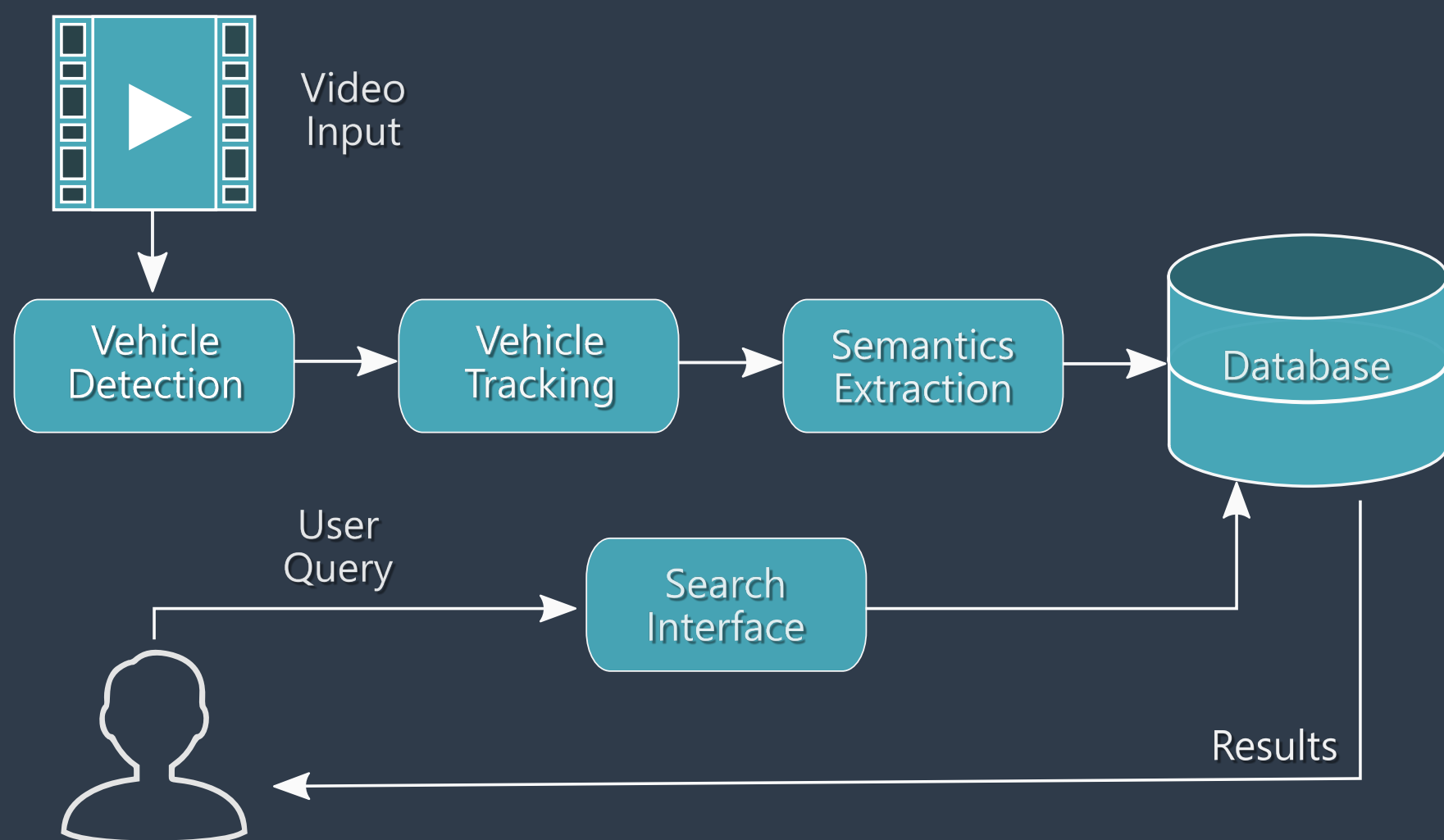
Carpark surveillance data

- vehicle color
- trajectories
- speed



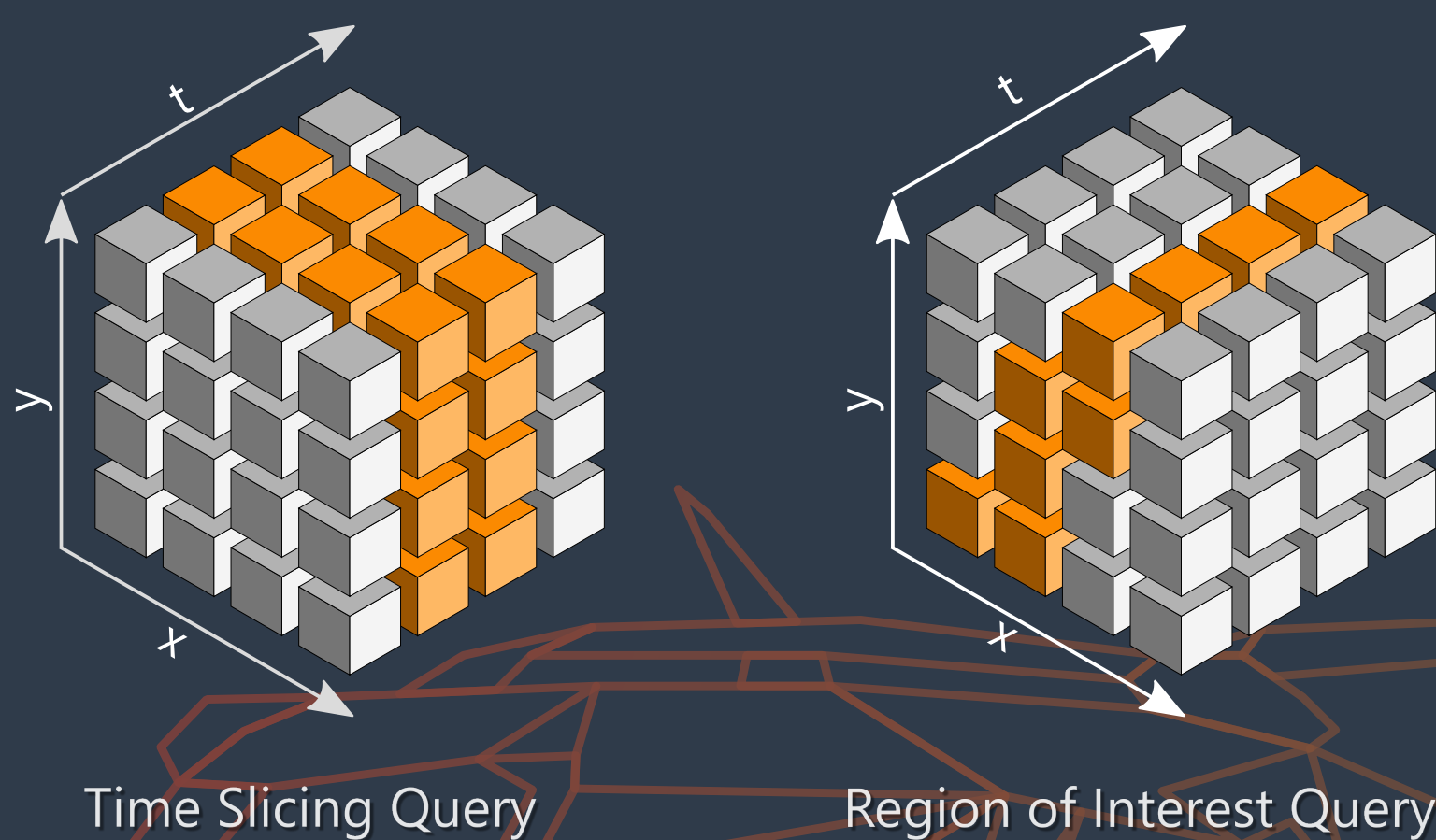
Challenges

- outdoor scenarios - various illumination & weather conditions
- retrieval time may increase as the data size grows



Key Concepts

- We adopted the concept of "atoms" - to quantize a video input into individual 3D spatial-temporal cubes which consist of the X-axis, Y-axis and T-axis.
- This enabled us to easily tag each vehicle with a unique sequence of atoms (x-position, y-position, and t-position).
- These sequence of atoms can then be used in the retrieval process based on the user-described motion of a particular vehicle.



Framework

Object Specific Semantic Extraction

- Color Information
- Motion Information

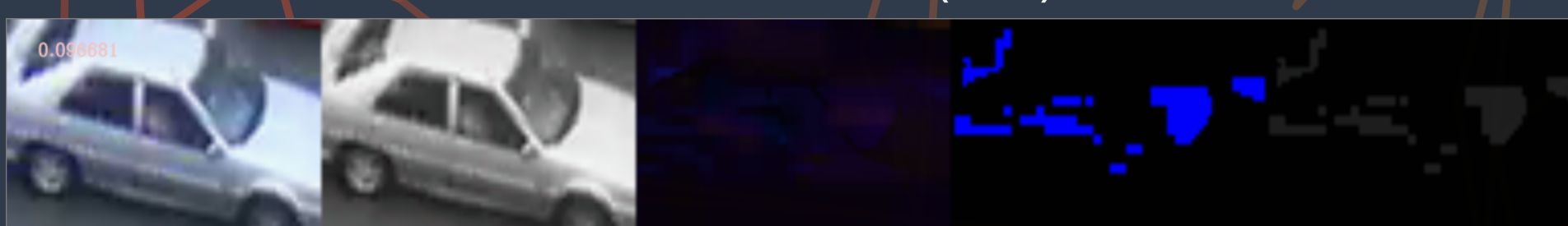
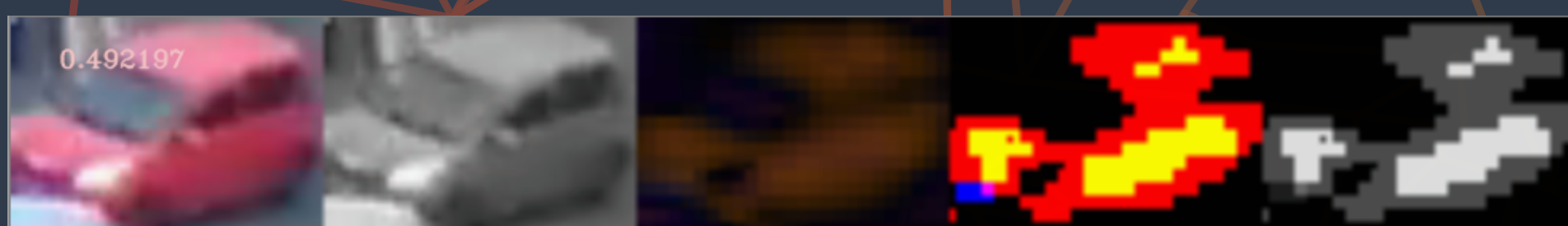


Fig: (From left) Original image; Grayscale image; Absolute difference; Binary threshold absolute difference; Threshold difference in grayscale

Color #	Gray	Black	White	Red	Blue	Orange	Yellow	Green	Pink	Purple	Brown
	365	182	150	60	19	15	13	10	9	7	7
%	43.6	21.7	17.9	7.2	2.3	1.8	1.6	1.2	1.1	0.8	0.8

Table: Ground truth distribution vehicle colors ordered by occurrence



Fig: (a) Black & White Filter Response, (b) 8+1 Directional Bins, (c) 11 Color Categories (Clockwise - Black, Gray, White, Red, Orange, Yellow, Purple, Pink, Brown, Blue, Green)

Experiment & Results

The method was tested on 2 days of continuous outdoor carpark data (20 hours, 10 each day). The performance is recorded as below.

		Predicted Color										
		Gray	Black	White	Red	Blue	Orange	Yellow	Green	Pink	Purple	Brown
Actual Color	Gray	236	61	68	0	0	0	0	0	0	0	0
	Black	48	134	0	0	0	0	0	0	0	0	0
	White	26	4	120	0	0	0	0	0	0	0	0
	Red	27	25	0	2	0	0	0	0	4	2	0
	Blue	3	10	0	0	6	0	0	0	0	0	0
	Orange	8	3	0	0	0	3	0	0	0	1	0
	Yellow	3	1	2	0	0	0	7	0	0	0	0
	Green	5	1	4	0	0	0	0	0	0	0	0
	Pink	1	0	0	3	0	0	0	0	5	0	0
	Purple	3	3	0	0	0	0	0	0	0	1	0
	Brown	3	4	0	0	0	0	0	0	0	0	0

Result	Precision	65.01	54.47	61.86	40.00	100.00	100.00	100.00	N/A	55.56	25.00	N/A
	Recall	64.66	73.63	80.00	3.33	31.58	20.00	53.85	0.00	55.56	14.29	0.00
	F1 Score	64.84	62.62	69.77	6.15	48.00	33.33	70.00	N/A	55.56	18.18	N/A

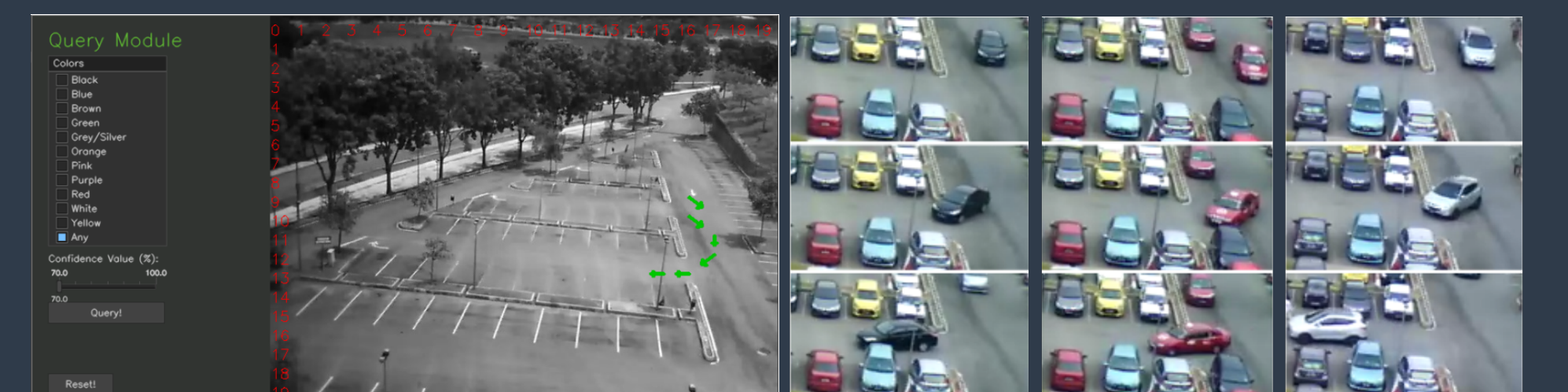


Fig: (left to right) Motion Test Case 2 (TQ2), Samples of 3 retrieved shots from Motion Test Case 2 (TQ2 - turning into a junction)

		CV: 70%			CV: 80%			CV: 90%		
		Precision	Recall	F1 Score	Precision	Recall	F1 Score	Precision	Recall	F1 Score
No. of Input	TQ1	5	93.82	61.53	74.32	95.34	33.19	49.24	95.34	33.19
		6	90.09	36.84	52.29	90.09	36.84	52.29	89.13	16.59
		7	87.27	38.86	53.78	88	17.81	29.62	87.87	11.74
	TQ2	4	86.88	21.45	34.41	84.61	13.36	23.07	89.65	10.52
		5	16.28	80	27.06	28.69	73.33	41.25	28.69	73.33
		6	65.3	71.11	68.08	73.33	48.88	58.66	73.33	48.88

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Selected References

- [1] Castañón, G., Elgharib, M., Saligrama, V., & Jodoin, P. M. (2016). Retrieval in Long-Surveillance Videos Using User-Described Motion and Object Attributes. IEEE Transactions on Circuits and Systems for Video Technology, 26(12), 2313-2327. Chicago
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