Automated traffic congestion estimation via public video feeds

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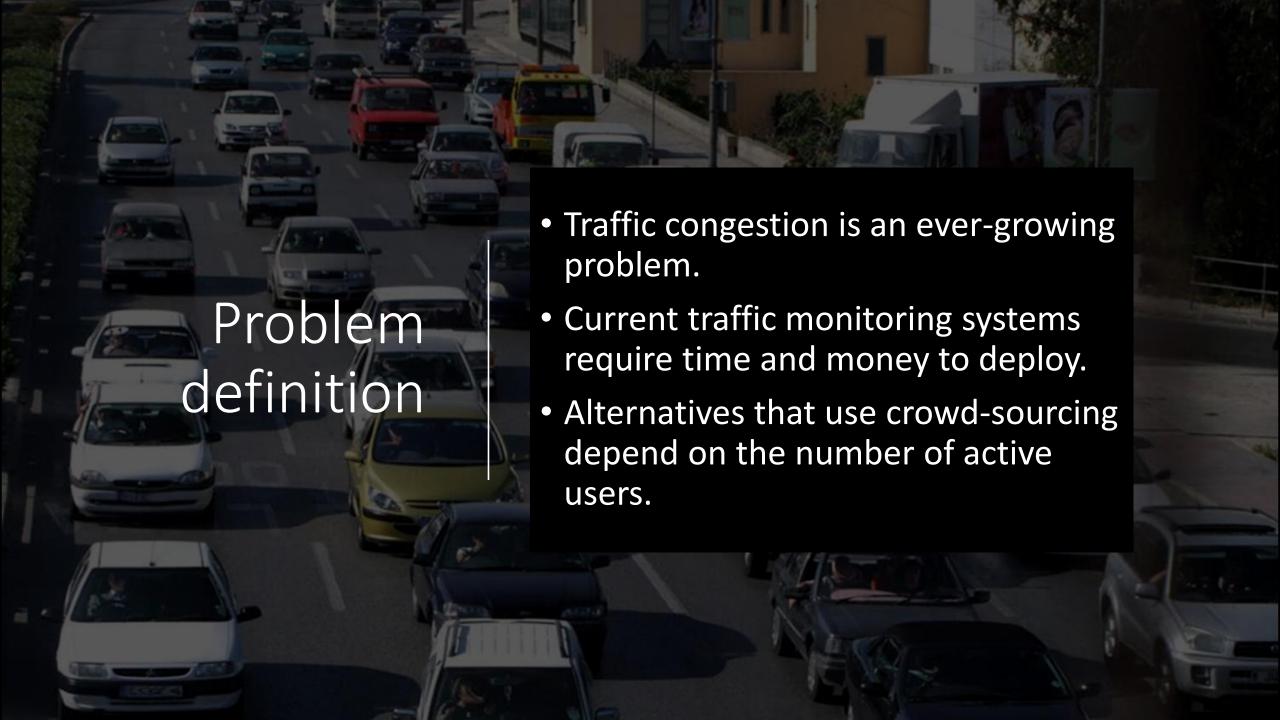
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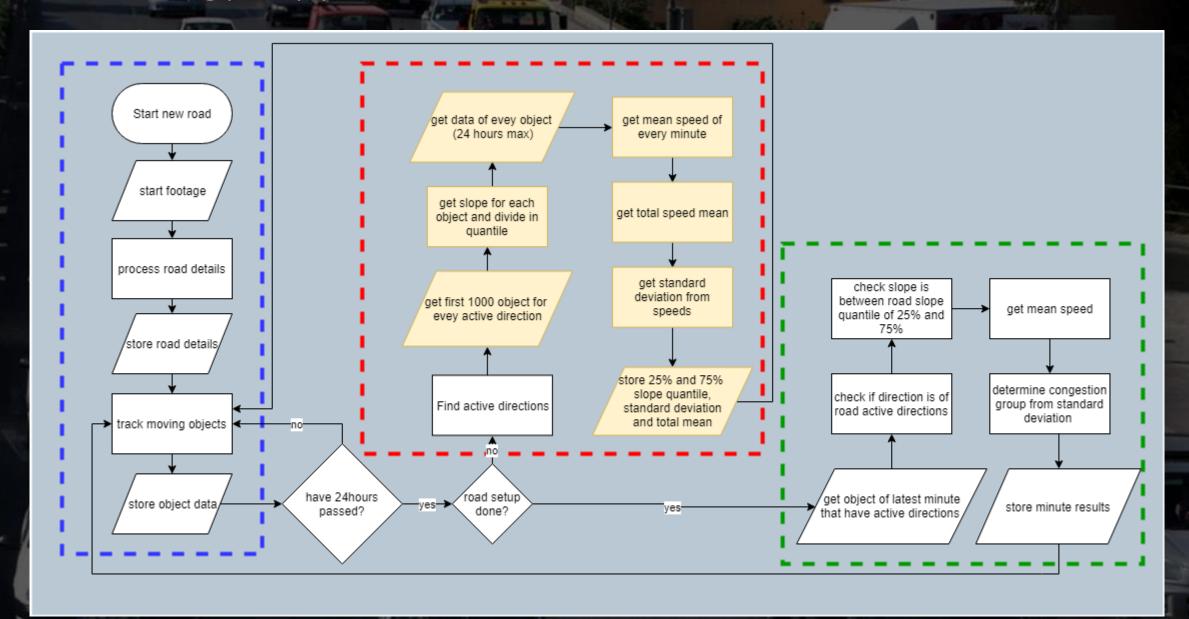








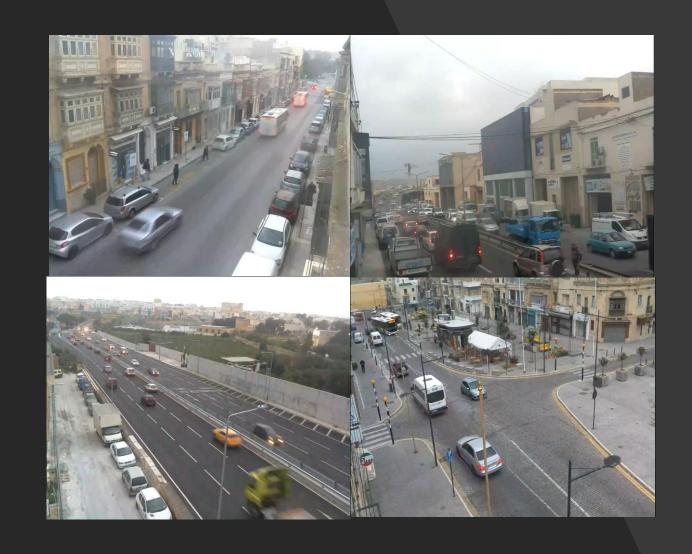
Methodology: Approach



Datasets

Video footage from four roads was collected to conduct test and a comparison with Google map's traffic

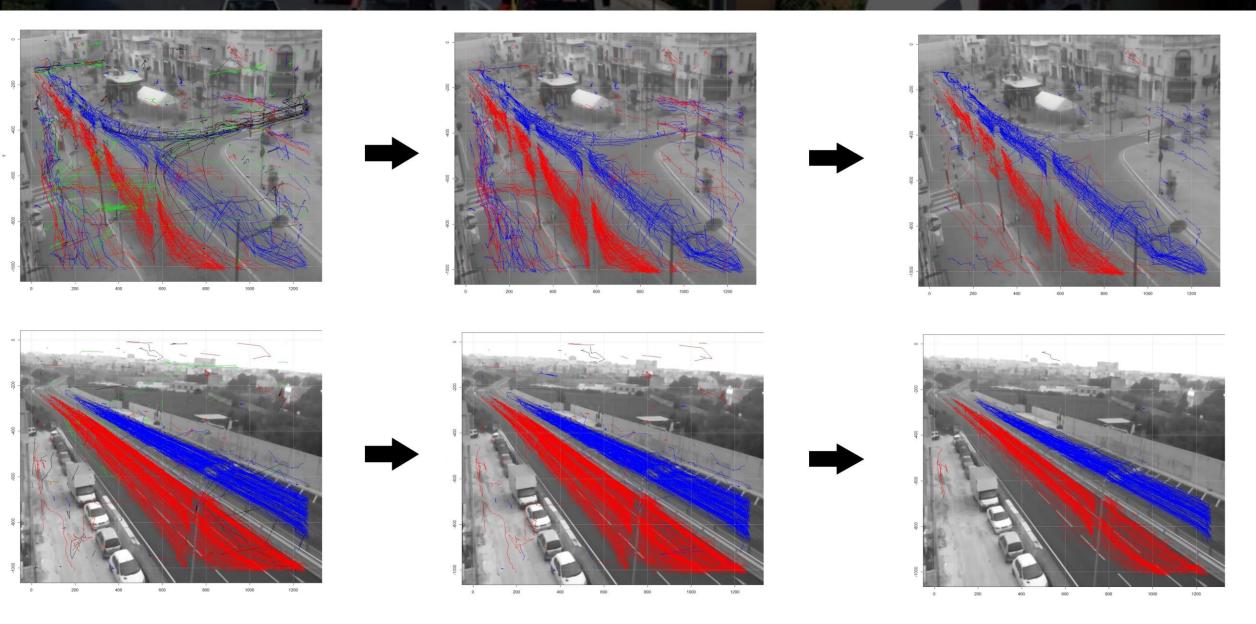
- 154 hrs of footage
- 408 video clips
- Recorded in 6 days



Tracked Paths

Direction filtering

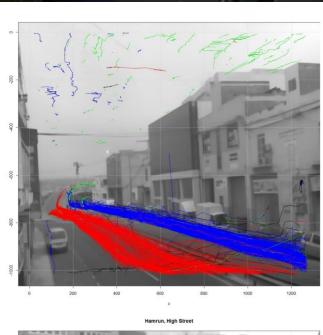
Slop filtering

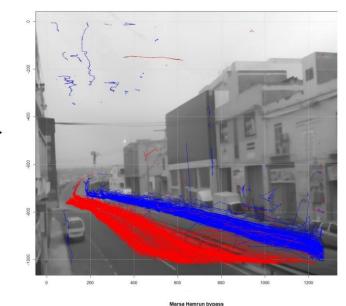


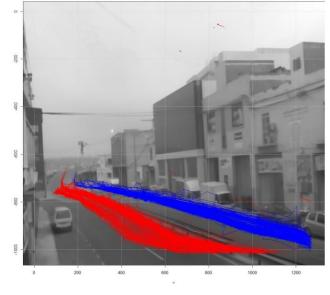
Tracked Paths

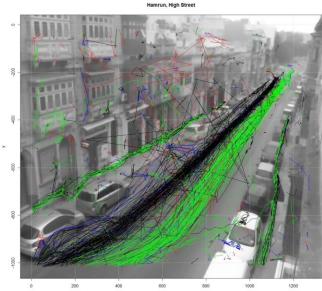
Direction filtering

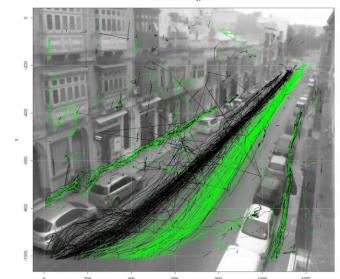
Slop filtering

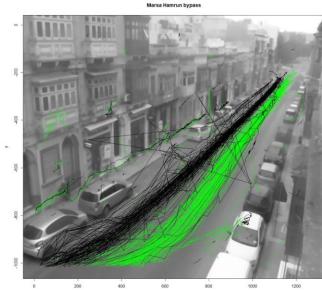






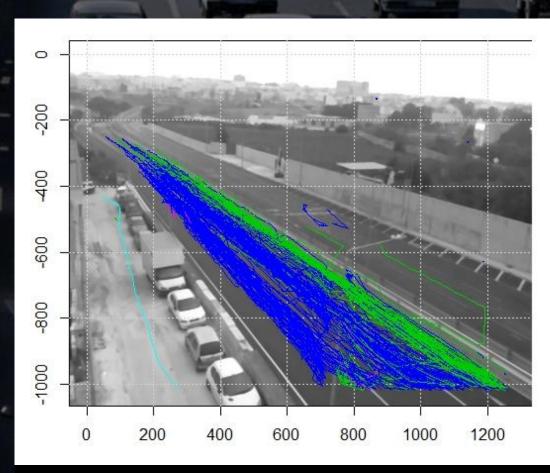




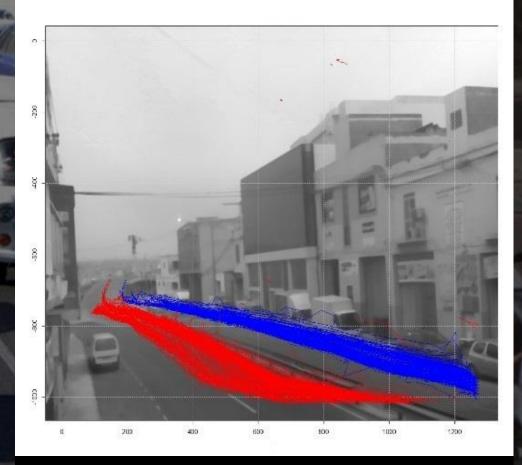




Lane detection with background reduction



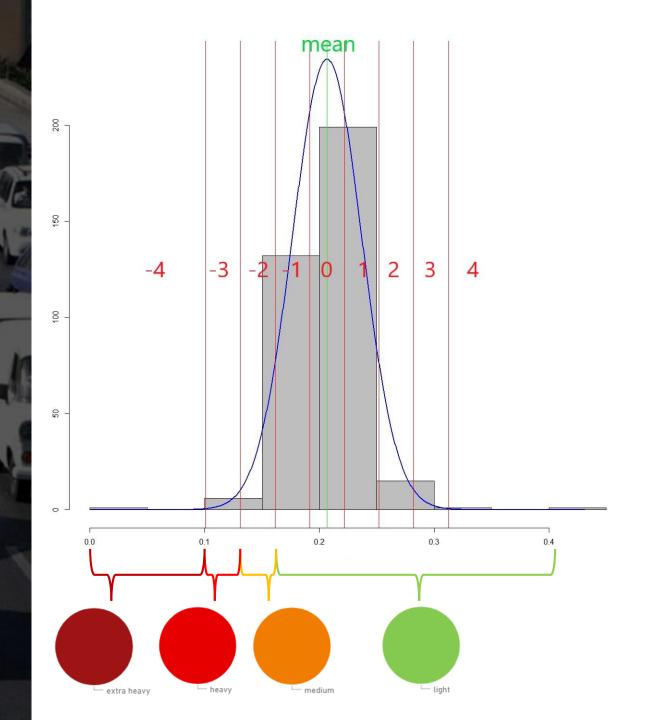
Unsuccessful unassisted lane detection



visualization of the difficulty to distinguish lanes

Traffic Flow classification

- Since we have no distance we used pixels per millisecond as speed
- Average speed form the first day of monitoring
- Standard Deviation from the average speed of every minute
- The standard deviation groups where further categorized in four groups



Our method compared to Google traffic and manual grading

	Accuracy	Precision	Recall	FPR	FNR	F1-Score
Weekday	85.49%	70.98%	70.98%	9.67%	29.02%	70.98%
Weekend	86.53%	73.06%	73.06%	8.98%	26.94%	73.06%

Our method vs Google Map's traffic, overall results

	Accuracy	Precision	Recall	FPR	FNR	F1-Score
Our Method	86.53%	73.06%	73.06%	8.98%	26.94%	73.06%
Google	78.37%	56.74%	56.74%	14.42%	43.26%	56.74%

Our method vs Google Map's traffic, overall results

Method	Runtimes	Processor	
Dynamic Texture Method	193	2.16 GHz dual core,	
Dynamic Texture Method	195	1GB RAM	
Macroscopic & Microscopic	119	2.16 GHz dual core,	
Parameters	113	1GB RAM	
Mixture of Dynamic Texture	8.19	NVIDIA Tesla C2070 GPU,	
Models		448 cores,	
Wodels		5376 MB Memory	
Block Variance	12.5	2.40 GHz Intel i3,	
Block variance	12.0	4 GB RAM	
Proposed Method	14.6	2.80 GHz Intel i37 quad core,	
1 Toposed Method		16 GB RAM	

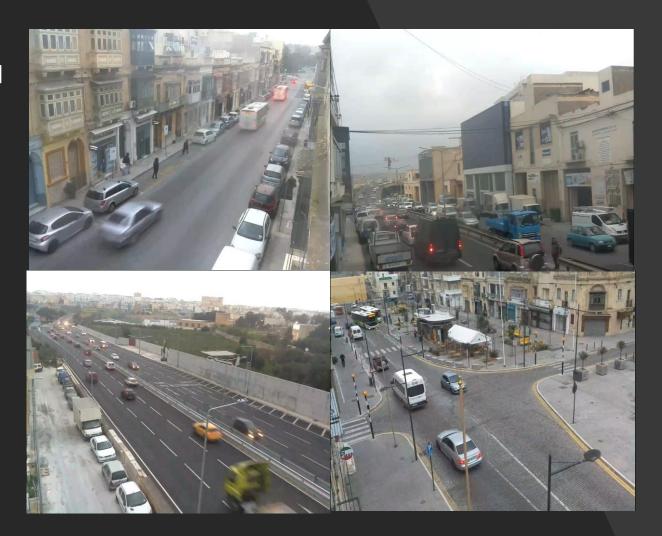
Performance comparison, from Garg et al. (2016)

THE RESERVE TO SERVE THE PERSON NAMED IN COLUMN TWO IS NOT THE PERSON NAMED IN COLUMN TWO IS NAMED	
google traffic	manual 🔻
light	light
heavy	heavy
light	light
extra heavy	medium
medium	light
	light heavy light extra heavy

Sample of comparison

Conclusion

- We successfully filtered the right directions and reduced pedestrian noise by the use of the path slop
- Successfully classified congestion in each road, with consistent results and improvement on Google map, especially in rural roads.
- Unassisted lane detection requires further research.
- Improved object detection can further improve results.



References

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Thank you

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