# Distributed Opportunistic Sensing and Fusion for Traffic Congestion Detection

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***Abstract*—Military data can be difficult to acquire owing to security and operational concerns, making it challenging to undertake research in 'Anticipatory Situational Understanding for Coalitions'. To help combat this, an analogous multi-modal, multi-agency, and distributed scenario has been created to support development of tools and techniques for detecting and predicting traffic congestion in the road transport network.**

**This scenario has been chosen as data is not generally available from a single unified source; different organizations (e.g. police, general public etc.) have sensors providing information of value. In this paper, we examine the problems of: a) identifying congestion using CCTV cameras; and b) fusing this with data from other agencies. In turn this can be used to supplement official transportation feeds. This coalition approach requires sensors to carry out assistive and supplementary tasks such as 'car counting' which this paper demonstrates how these can be done using deep learning neural networks. Utilizing distributed data sources will provide approaches that are generalizable and ad-hoc therefore more appropriate to a military context.**

**An initial four-layer architecture and tooling are set out to enable rapid formation of human/machine hybrid teams, with a focus on opportunistic and distributed processing at the edge of the network.**

## I. Introduction

Congestion is an indicator that a transport network is either routinely not fully meeting the needs of the users or it is being disrupted by an extraordinary occurrence such as an accident or major public event. Transport network users and maintainers desire increasingly fine-grained real-time visibility of the evolving network based on actual usage, and the potential for harvesting this data from distributed devices in addition to bespoke ancillary systems.

Multiple data sources can play a role in detecting congestion, spanning multiple modalities, such as traffic cameras, public transport data, weather *etc*. However, the sources may not all be under a single authority or organization, requiring establishment of a 'coalition' of related sources and information processing. By accounting for such a 'coalition of sources' in a situational awareness solution there is opportunity to enhance the situational picture and go beyond perception into comprehension and projection.

To advance our 'coalition of convenient sources' perspective, a multimodal dataset has been gathered using publicly accessible temporally and spatially coordinated data feeds which are distributed both geographically and organizationally, i.e. the data sources converge on a common geographic region but are provided by different coalition partners. Some techniques for the analysis of this data are proposed as well as a high-level architecture for how these distributed sensors and underlying uncertainty could be fused to provide a holistic map of congestion across the sensed network and beyond.

## II. Summary of Prior Art

With the recent explosion in sensor availability both the body of knowledge and the associated data sources will increase . Obvious starting points are the metrics used to determine congestion from simple determinations such as stream speed [1] to more complex characterizations such as a Traffic Congestability Value (TCV) [2], as well as how congestion propagates across the network [3] and designing networks to be congestion resistant.

Our research in this space is focused specifically on opportunistic, distributed sensing, in particular alongside the use of *machine learning / deep learning* tools, in scenarios where common computational modes or tooling may not be shared among all partners. Of clear relevance to this are some interesting studies using more traditional toolsets on existing map service providers to provide wider indications of congestion [4], [5], as well as other facets such as SVM [6], HMM Models [7], multi-agent based models [8], long short-term memory [5], and backpropagation (BP) Neural Networks [9].

## III. Description of Datasets

To support the development and evaluation of the proposed techniques a multi-modal dataset has been gathered bringing together temporally and geographically aligned data from public datasources. London (UK) was chosen as there were a number of appropriate data feeds which were accessible to researchers, mainly via the Transport for London (TfL) API [10] which provides access to traffic cameras (still and video), live bus updates, air quality, cycle data, and more. The CCTV image and video data is collected every 5 minutes with a 10 second video clip and a single still image being available for each of the approximately 1000 CCTV cameras with a publicly available live feed. Each day of collection sees around 33GB of video data, 5GB of still images, and 750MB of other sensor data captured, totalling around 40GB. This has been gathered continuously since February 2017 in order to create a consistent dataset for machine learning and pattern-of-life model building.

## IV. Proposed Analysis Tools

Not all the multi-modal inputs can be readily fused to determine congestion. A lot of value resides in the imagery data in particular, and work has been done investigating how existing deep learning techniques can be applied to enhance other image processing techniques to understand the congestion indicated directly in the static images and video.

To address this problem, we use regional-convolutional neural network (R-CNN) for car detection and counting. R-CNN can be used to localize and detect *multiple* objects within the input image. While the same thing can, in theory, be achieved by using CNN to classify different sliding windows inside the given image, this approach is too computationally expensive. R-CNN provides a computationally efficient solution for localizing and detecting objects in the image. Fine-tuning of the pre-trained model using images sampled from our dataset is planned as well as modification of the model architecture to keep only output classes that are valid for the congestion detection problem.

## V. High Level Architecture

In order to manage and fuse these sensor feeds, a high level architecture is proposed, consisting of four hierarchical layers. Each of these layers is virtual and can span multiple agencies within a coalition.

### A. Data Sources Layer

The *data sources* layer is made up of heterogeneous data sources provided by a range of sensors, modalities, and collection platforms. Ownership for each source may lie with different members of the coalition who grant access as required, or any source could be publicly available and therefore open source in nature. Many additional capabilities and complexities can be inserted into this layer of the architecture, for example through using fine-grained policy based access control to allow each member of the coalition to share their sources explicitly with certain other partners only.

### B. Information Processing Layer

At the *information processing* layer, processing services are maintained and shared by the partners of the coalition. These services are responsible for producing initial conclusions from the input data provided by the coalition data sources.

This enables the inherent uncertainty arising from this basic processing to be explicitly captured and bound to the resulting information to provide additional accountability and transparency in any subsequent usage, and to better enable the interpretability of results later in the pipeline.

### C. Knowledge Representation Layer

The *knowledge representation* layer contains all processes relating to the semantics or meaning of the data. This is also the layer where the human users have the most opportunity to inject their human knowledge into the system, enabled via the tellability function in the uppermost layer. Different models and techniques can be used in the knowledge representation layer to fulfill different kinds of processing and many of these can be integrated to enable high-value outcomes.

### D. Decision Support Layer

The final layer, *decision support*, allows the user agent to utilize the resources in the layers below. Unlike the lower layers, which consists of services distributed across the coalition, each agent would have their own instance of a user interface which would enable querying of the available services to assist in the tasks of the agent.

## Acknowledgement

This paper is based on content previously published in [11].

This research was sponsored by the U.S. Army Research Laboratory and the UK Ministry of Defence under Agreement Number W911NF-16-3-0001. The views and conclusions contained in this document are those of the authors and should not be interpreted as representing the official policies, either expressed or implied, of the U.S. Army Research Laboratory, the U.S. Government, the UK Ministry of Defence or the UK Government. The U.S. and UK Governments are authorized to reproduce and distribute reprints for Government purposes notwithstanding any copy-right notation hereon.

## References

[1] A. M. RAO and K. R. RAO, "Identification of traffic congestion on urban arterials for heterogeneous traffic." *Identificacion de la congestion del trafico en las zonas urbanas para el trafico arterials heterogeous.*, vol. 11, no. 3, pp. 131–142, Jul. 2016.

[2] Patel Nilanchal and Mukherjee Alok Bhushan, "Assessment of network traffic congestion through Traffic Congestability Value (TCV): a new index," *Bulletin of Geography: Socio-Economic Series, Vol 30, Iss 30, Pp 123-134 (2015)*, no. 30, p. 123, 2015.

[3] H. Nguyen, W. Liu, and F. Chen, "Discovering Congestion Propagation Patterns in Spatio-Temporal Traffic Data," *IEEE Transactions on Big Data*, vol. PP, no. 99, pp. 1–1, 2016.

[4] C. Bian, C. Yuan, W. Kuang, and D. Wu, "Evaluation, Classification, and Influential Factors Analysis of Traffic Congestion in Chinese Cities Using the Online Map Data." *Mathematical Problems in Engineering*, pp. 1–10, Sep. 2016.

[5] Y.-y. Chen, Y. Lv, Z. Li, and F. Y. Wang, "Long short-term memory model for traffic congestion prediction with online open data," in *2016 IEEE 19th International Conference on Intelligent Transportation Systems (ITSC)*, Nov. 2016, pp. 132–137.

[6] H. N. Nguyen, P. Krishnakumari, H. L. Vu, and H. v. Lint, "Traffic COngestion pattern classification using multi-class SVM," in *2016 IEEE 19th International Conference on Intelligent Transportation Systems (ITSC)*, Nov. 2016, pp. 1059–1064.

[7] F. Porikli and X. Li, "Traffic congestion estimation using hmm models without vehicle tracking," in *IEEE Intelligent Vehicles Symposium, 2004*, June 2004, pp. 188–193.

[8] A. Lakhouili, E. H. Essoufi, and H. Medromi, "Multiagent based model for urban traffic congestion measuring," in *2015 5th World Congress on Information and Communication Technologies (WICT)*, Dec. 2015, pp. 73–77.

[9] X. Yu, S. Xiong, J. Xiang, J. Mao, M. Liu, and Y. Zhao, "A Campus Traffic Congestion Detecting Method Based on BP Neural Network," in *2015 2nd International Symposium on Dependable Computing and Internet of Things (DCIT)*, Nov. 2015, pp. 93–100.

[10] Transport for London, "Transport for london unified API." [Online]. Available: https://api.tfl.gov.uk/

[11] A. Nottle, S. Quintana-Amate, D. Harborne, M. Alzantot, D. Braines, R. Tomsett, L. Kaplan, M. Srivastava, S. Chakraborty, and A. Preece, "Distributed opportunistic sensing and fusion for traffic congestion detection," in *First International Workshop on Distributed Analytics InfraStructure and Algorithms for Multi-Organization Federations*, 2017.