THE COOPER UNION FOR THE ADVANCEMENT OF SCIENCE AND ART
ALBERT NERKEN SCHOOL OF ENGINEERING

Computer Vision for Vehicle Emission Estimation

By

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This thesis was prepared under the direction of Carl Sable and has received approval. It was submitted to the Dean of the School of Engineering and the full Faculty, and was approved as partial fulfillment of the requirements for the degree of Master of Engineering.

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Abstract

Hello

Contents

1 Introduction

1.1 Motivation

Urban air pollution remains one of the most critical public health and environmental challenges of the twenty-first century. The World Health Organization (WHO) estimates that approximately 99% of the global population breathes air containing pollutant concentrations that exceed guideline limits [1], [2]. In 2023 alone, air pollution contributed to 7.9 million deaths worldwide, with 86% of these attributed to noncommunicable diseases such as cardiopulmonary conditions and lung cancer [2]. Beyond its immediate health impacts, atmospheric pollution catalyzes broader environmental degradation. Short-lived climate pollutants and greenhouse gases contribute to global warming, weather variability, and the intensification of the water cycle, which in turn threatens infrastructure and coastal settlements [3], [4].

Road vehicles are the central driver of both the climate and health aspects of this crisis. The Intergovernmental Panel on Climate Change (IPCC) Sixth Assessment Report notes that direct greenhouse gas (GHG) emissions from the transport sector accounted for 23% of global energy-related CO_2 emissions in 2019 [5]. Of these, 70% originated specifically from road vehicles [5]. Without intervention, transport emissions are projected to double by 2050, driven by increasing vehicle ownership in developing economies [6]. In urban environments, these emissions are particularly consequential because they are released at ground level along the very corridors where people live, work, and commute, creating immediate exposure risks [3].

New York City (NYC) serves as a critical intersection of dense population, heavy traffic activity, and measurable health burdens. As of July 2024, there are 8.48 million residents in all five boroughs, with (x amount of people near major roadway/highway that is high risk exposure. ASK SABLE: should I try to find the number for this if I have the time? Like should I try to contribute as much as I can? I can't find a number past 2007) [7]. While the typical passenger vehicle emits approximately 411 grams of CO_2 per mile [8], it also releases pollutants toxic to human health, most notably fine particulate matter ($PM_{2.5}$). This pollutant is described by the NYC Department of Health and Mental Hygiene as "the most harmful air pollution for humans to breathe" as $PM_{2.5}$ penetrates deep into the lungs and enters the bloodstream, circulates throughout the body, and causes systemic inflammation [9].

The local impact of these emissions is quantifiable and severe. In New York City, $PM_{2.5}$ levels from all sources contribute to approximately 2,000 deaths and 5,150 emergency department visits annually [9]. 14% of local $PM_{2.5}$ is directly attributable to everyday car, bus, and truck traffic, resulting in an estimated 320 premature deaths and 870 hospitalizations each year [9]. In New York State, the combined health and climate costs attributable to passenger vehicles totaled approximately $7.9 billion in 2015, with health-related costs comprising two-thirds of that total [10].

Despite the well-documented impacts of transportation emissions, effective mitigation is hindered by the difficulty of accurate, timely measurement. Emissions from road vehicles are not distributed uniformly across space or time, but rather concentrated in specific "hotspots," vary by time of day, and depend heavily on vehicle composition. For instance, heavy-duty vehicles contribute disproportionately to nitrogen oxides (NOx) and particulate matter relative to light-duty cars [11], while congestion increases per-mile emissions through idling and stop-and-go driving. Consequently, understanding not only total vehicle counts but also the specific composition of traffic flows is critical for estimating localized emissions burdens.

Traditional emissions estimators, however, often rely on aggregate fleet statistics and modeled travel demand applied at coarse spatial scales. While indispensable for long-term planning, these methods often lack the granularity required to evaluate street-level exposure disparities. Similarly, fixed air-quality monitoring stations measure ambient concentrations but cannot directly attribute pollutants to specific vehicle classes or immediate traffic patterns. Furthermore, monitoring infrastructure is unevenly distributed globally. High-income regions typically possess denser monitoring networks, whereas many low- and middle-income countries lack adequate coverage, leaving large populations without reliable local air quality data [12].

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To address these limitations, this thesis proposes leveraging existing video infrastructure as a scalable monitoring tool. New York City maintains an extensive network of publicly accessible traffic cameras, offering a unique opportunity to generate high-resolution data without deploying new hardware. By applying computer vision techniques to identify vehicle classes and counts, combined with established emission factors, it is possible to generate spatially resolved estimates of traffic-related emissions. This approach does not replace traditional air-quality monitoring but complements it, providing a granular view of how traffic composition drives environmental health impacts. Moreover, this methodology offers a potential blueprint for regions with limited monitoring resources, suggesting that computer vision-based estimation could become an accessible, scalable tool for global environmental health monitoring.

2 Related Work

2.1 Traditional Air Quality Monitoring Methods

This section reviews the evolution of methodologies for quantifying urban air pollution, ranging from traditional stationary infrastructure to deep learning approaches. It evaluates the strengths and limitations of direct measurement approaches. It identifies the critical data gaps in spatial resolution and source attribution that necessitate the development of high-resolution, vision-based bottom-up inventories.

Rewrite: Current approaches to urban air quality assessment are generally categorized into top-down and bottom-up methodologies. Top-down approaches infer emission fluxes from observed atmospheric concentrations, using data from satellite remote sensing or stationary monitoring networks to validate regional models. Conversely, bottom-up approaches calculate emissions at the source by combining activity data (e.g., traffic flow) with emission factors. This section reviews the evolution of these monitoring paradigms, evaluating the limitations of current top-down observation in resolving street-level heterogeneity and identifying the critical need for high-resolution, vision-based activity data to improve bottom-up inventories.

2.1.1 Stationary Air Quality Monitoring Stations (AQMS)

Regulatory-grade stationary networks are the standard for air quality assessment, providing high-quality, standardized data ideal for analyzing spatiotemporal trends across large regions [1]. However, the number of these fixed-site monitors are limited. For example, in U.S. urban areas with continuous monitoring, there are typically only 2-5 monitors per million people [2]. Consequently, they fail to capture hyperlocal, street-by-street variations in pollution, which is the scale at which human exposure and exceedances of ambient standards often occur [1], [2]. Research indicates that concentrations of pollutants such as ultrafine particles (UFP), black carbon (BC), and nitrogen oxides (NO_x) can vary by 5–8 times within individual city blocks and fluctuate significantly over distances of less than 300 meters [1], [2]. While dispersion models and satellite remote sensing are often used to supplement stationary data, they face intrinsic resolution limitations (discussed further in Section 2.2). Thus, they cannot fully resolve the fine-scale gradients (10–300 m) driven by local traffic emissions [2].

2.1.2 Mobile Monitoring Platforms

To address the spatial limitations of fixed networks, mobile monitoring (mounting reference-grade instruments on fleet vehicles) has emerged as a method to capture high-resolution spatial data [1]. Notable implementations include equipping Google Street View cars to repeatedly sample urban roadways, successfully revealing persistent pollution patterns and stable ”hotspots” attributable to local sources [2]. This approach allows for the identification of source impacts without a priori assumptions about emission rates [1].

However, while mobile monitoring maximizes spatial coverage, it lacks temporal continuity [1]. Because a vehicle cannot measure all locations simultaneously, data must be aggregated over long periods or modeled to estimate averages [1]. Furthermore, measurement locations are inherently biased toward the roadway (on-road), which can differ from off-road concentrations (e.g., at home addresses) by 20–30%, necessitating careful adjustment when estimating population exposure [1].

2.1.3 Low-Cost Sensors and On-Board Diagnostics (OBD)

A shifting paradigm in monitoring involves the deployment of portable, lower-cost sensors capable of reporting near real-time data [3]. These devices are generally categorized into gas-phase sensors (electrochemical or metal oxide) and particulate matter sensors (optical scattering) [3]. While these allow for denser deployment and community-based science, they suffer from significant data quality issues. As of April 2026, there are currently no commercially available direct-reading sensors for PM mass (relying instead on light-scattering surrogates) or specific hazardous air pollutants, and performance criteria for non-regulatory use remain undefined [3].

Similarly, the mandatory equipping of heavy-duty vehicles with On-Board Diagnostic (OBD) systems offers a potential stream of ”big data” for real-time emission monitoring [4]. While this provides an opportunity to supervise in-use vehicles remotely, the data quality is often poor and lacks a comprehensive assessment, requiring substantial computational infrastructure to process effectively [4].

2.2 Satellite-Based Remote Sensing

While sensor networks provide point-based measurements, satellite remote sensing offers a top-down approach to air quality monitoring, playing a critical role in developing emission policies and forecasting regional air quality [5], [6].

2.2.1 Resolution and Instrumentation

The landscape of satellite monitoring has shifted with the deployment of instruments like the Tropospheric Monitoring Instrument (TROPOMI) on the Sentinel-5P mission. TROPOMI provides daily global measurements at an unprecedented spatial resolution of approximately 3.5×5.5 km^2, allowing for the detection of trace gases (NO_2, O_3, CO) and their linkages to human activity [7], [8]. Complementary infrared sounders, such as IASI and AIRS, provide vertical profile data, though at coarser footprint resolutions (12 km) [9]. Despite these advancements, even "high-resolution" satellite data remains too coarse (¿3 km) to resolve the fine-scale gradients (10–300 m) driven by urban traffic emissions, effectively smoothing out the street-level heterogeneity that defines urban exposure [2], [10].

2.2.2 Physical and Environmental Constraints

Beyond spatial resolution, satellite retrieval is limited by physical constraints, particularly regarding diurnal variation. "Top-down" observation is highly sensitive to the planetary boundary layer height; in the morning, a shallow boundary layer can mask surface-level pollutants, reducing sensitivityexactly when traffic emissions are often highest [10]. Furthermore, retrieval algorithms struggle with environmental variables such as surface reflectivity and viewing geometry (zenith angles), which can introduce artifacts into the data, particularly at high latitudes or in complex urban terrains [10].

2.2.3 The Dependency on Bottom-Up Inventories

To bridge the gap between regional satellite data and street-level reality, researchers rely on chemical transport models (CTMs) and data assimilation techniques. However, the efficacy of these models is fundamentally limited by the quality of their inputs. Recent reviews indicate that high-resolution CTMs require detailed emission inventories (better than 1 km resolution) to resolve small-scale dynamical features like urban heat islands and street canyon effects [10]. The current lack of such granular, dynamic ”bottom-up” inventories remains a bottleneck for effective satellite data assimilation, validating the need for improved terrestrial emission modeling [10], [11].

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