

AutoWaze: Towards Automatic Event Inference in Intelligent Transportation Systems

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Abstract—Traffic monitoring is one of the key challenges in Intelligent Transportation Systems (ITS). In this paper, we propose to build a crowdsourcing application for traffic monitoring. The novelty of the proposed approach is that visual data is collected to enable automatic event inference with the recent advance in Computer Vision. The challenge is that mobile devices are not capable of handling visual task processing in high accuracy. We propose to build a networked system so that mobile devices can offload data via available wireless access interfaces (e.g., 4G LTE, WiFi, DSRC) to edge servers, e.g., GENI Rack. We plan to use the testbed at Kettering University to validate the proposed approach.

Index Terms—Spatial crowdsourcing, Intelligent Transportation Systems, Edge Computing

I. INTRODUCTION

Traffic monitoring is a key task in Intelligent Transportation Systems (ITS). Most existing monitoring systems are infrastructure-based systems, deploying dedicated traffic sensors, e.g., cameras, radars, etc., at fixed locations. However, infrastructure-based systems are very expensive, and thus sensors are only deployed in highways, major urban streets, and large intersections. For example, a radar speed sign will cost around \$3000 [1]. As a result, these systems cannot collect sufficient traffic information, particularly for large urban areas consisting primarily of smaller streets.

Nowadays, crowdsourcing-based navigation applications, e.g., Google Map [2] and Waze [3], are widely used by drivers. Drivers usually mount smartphones on the windshield before driving and get real-time updates during their trip. *One of the significant advantages is that navigation apps utilize millions of users (i.e., crowds) to collect traffic information.* Compared with the infrastructure-based systems, navigation apps collect traffic-related data from all running users and thus have roads' traffic information on major streets and smaller streets. For instance, Waze builds a live map where a Waze user can report real-time traffic information, e.g., accidents, road hazards, traffic jams, so that other Waze users can further calculate the fastest route based on the real-time traffic updating [3].

In this abstract, we propose a traffic monitoring crowdsourcing system, i.e., AutoWaze, which utilizes the mounted smartphone in the windshield to collect *visual data*. The collected visual data can be analyzed automatically with Computer Vision technique to support real-time traffic monitoring and safety-related alerts in intelligent transportation systems.

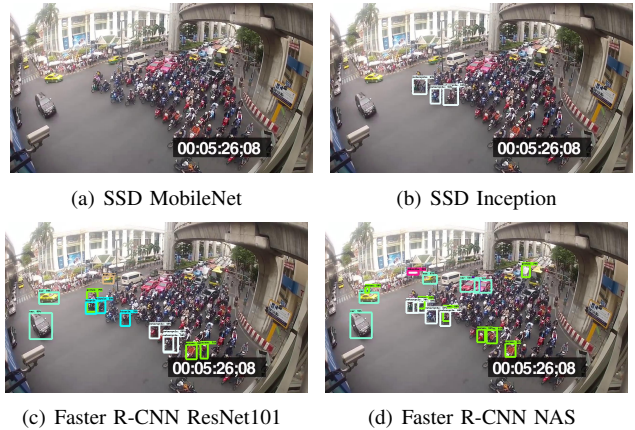


Fig. 1. Detection results of four object detection models

As a result, it addresses several drawbacks of navigation applications with the human operation (e.g., Waze). First, reporting traffic-related events by drivers manually can be distracting, and thus, it is not safe. According to [4], as a user reporting an event currently needs some screen time, even two seconds on the phone can cost a driver loss of attention for ~ 30 meters (assuming 60 km/hour speed). Second, it will be tough for a driver to report events in complicated road condition. Third, there are only several categories and thus, the information provided by the crowds is limited.

II. RESEARCH PLAN

A. Challenges

The major challenge of using visual data is due to weak computation power of smartphones. The reason is that the actual road situation might be extremely complicated. To fully understand the current case, we need to hand-code millions of variables in real-time. Notably, the weak computation power of the smartphone cannot handle traffic detection in a real-time manner and thus limits us from developing more sophisticated applications. We ran some tests by using four state-of-the-art object detection models on a Traffic CCTV camera in Bangkok Thailand [5] and the results are shown in Fig. 1. The SSD MobileNet simply detect nothing in a complex scenario. However, according to [6], mobile devices can only handle lightweight object detection models, e.g., SSD MobileNet and SSD Inception rather than more sophisticated models, e.g., Faster R-CNN Inception and Faster R-CNN NAS.

TABLE I
A COMPARISON BETWEEN THE PROPOSED APPROACH WITH THE EXISTING APPROACH

	Collected data	Comm. Interface	Advantage	Challenges	Human interaction
Google Map	GPS, cellular data	Cellular	small data size	high estimation error	No
Waze	GPS, cellular data, human event report	Cellular	small data size	driver distraction, limited event category	Yes
AutoWaze	Visual Data, GPS, vehicle sensor readings	Cellular, WiFi, DSRC, etc.	fine-grained description, automatic event recognition	Big data size, weak phone computation power	No

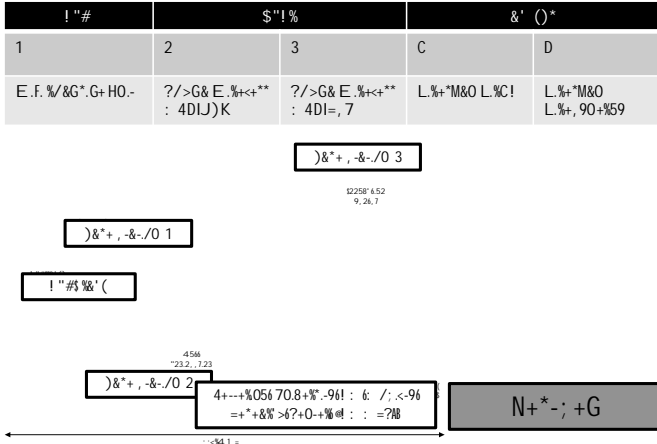


Fig. 2. Experimental testbed at Kettering University.

B. Proposed Approach

We plan to build a networked system, which can perceive the traffic event with the minimum human operation and communicate with servers to get timely result. It takes advantage of the wide availability of multiple sensors (e.g. cameras, ultrasonics, radar, GPS, etc. [7, 8]), computation (e.g., multi-core CPU architecture and powerful GPUs) and communication resources (e.g., DSRC [9], WiFi, 4G/LTE [10], and other licensed/unlicensed spectrum [11]) of smartphones or modern vehicles. A comparison between the proposed method and existing approaches is shown in Table I.

To leverage the limited computation power of smartphones, we proposed to build a networked system. We assume a typical Vehicle-to-Everything (V2X) communication environment in the intelligent transportation system [12], where there are two types of interfaces (i.e., proximity-based communication interfaces (e.g., WiFi, DSRC) and the cellular communication interface) [13, 14]. The mounted smartphone in the vehicle or the vehicle, if there is no confusion, can communicate with remote servers through nearby vehicles, roadside infrastructures, e.g., the Roadside Unit (RSU), through proximity-based communication in an ad hoc manner if they are available. On the other hand, the smartphone can communicate with servers through the cellular network at any time. We plan to address the cellular monetary cost, inference latency and inference accuracy trade-off in the proposed system.

C. Experimental Platform

We have a 4G-LTE testbed facility and two Chevrolet Bolt EVs at Kettering University. We have a master agreement to access Sprint's 4G LTE 38 and 41 bands (2:510 MHz, 2:520

MHz, and 2:530 MHz frequencies). As shown in Fig. 2, there are 5 base stations installed in 3 different locations across Kettering University campus area. There are 3 Air4G antennas on the roof of Academic Building with the coverage range about 1.5-2 miles. Other 2 AirSynergy antennas are located on the roof of Mott Engineering Building and Innovation Center, respectively. The AirSynergy antenna's coverage range is about 1-1.5 miles. This 4G-LTE system fully covers Kettering University GM Mobility Research Center, which is a 21 acre outdoor vehicle test track. In addition, the DSRC (Cohda Wireless MK5) and WiFi Ad Hoc RSUs can be used to conduct proximity-based communication experiments. This test system is also connected with a backend GENI rack, where we can run Deep Neural Networks (DNNs) to get inference result at high accuracy.

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