Poster: Soft-Swipe: Enabling High-Accuracy Pairing of Vehicles to Lanes using COTS Technology

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ABSTRACT

In this paper we demonstrate a novel system Soft-Swipe, which can enable highly accurate pairing of vehicles to respective lanes in a wide-range of vehicle-based multi-lane service stations using economical general-purpose commodity communication and sensing technology. To study the system, we consider an example application of pairing vehicles to respective quality check bays in an automobile manufacturing plant. Our proposed system called Soft-Swipe works by matching natural signatures (specifically, motion signatures) generated by the target object with the same signature detected by simple instrumentation of the environment (a video camera). Soft-Swipe is the first work that accurately captures the fine grain motion profile of vehicles using commodity hardware to provide vehicle-to-infrastructure pairing.

1. INTRODUCTION

In this paper we explore applications in which interactions originate from within a vehicle to pair or authenticate to respective lanes for enabling wide range of electronic transactions. Transacting from within a vehicle can lead to shorter wait times and higher system throughput. Further, in many situations, the user would be thankful for reduced exposure to inclement weather conditions. The applications can be broadly categorized as follows. **Class-I (Temporary infrastructure):** Customized parking information display and parking payments for temporary events such as football games, circus, fair, etc. are usually processed manually (both payer and payee) and easily lead to heavy backlog in traffic whose effect can extend for several miles. **Class-II (Small-scale infrastructure):** Application scenarios where the infrastructure is owned by small players can be categorized as follows: *1) Vehicle-specific services:* Customized information display and payments for services such as car-wash, automated fueling, automated swapping of car batteries for Electric Vehicles (EVs), automated battery charging centers for EVs, and parking charges can be made from within the vehicle. In an automotive manufacturing plant, a vehicle arriving at a manufacturing station needs to be correctly identified so that the appropriate set of tests can be conducted and the appropriate actions can be taken by the assembly line robots or humans. *2) User-specific services*: Customized information (past orders etc.) and payments for drive-thru services such as fast-food, or DVD rental can be supported by such a system. A bank customer can perform automatic verification from inside the vehicle before reaching the ATM machine. Today for such applications usually the payer stops the vehicle to use a machine to make the payment. **Class-III (Large-scale infrastructure):** Highway toll collection systems can afford to deploy various types of expensive equipment such as directional RFID readers, laser sensors and inductive loops. Widely used examples of such systems include E-Z Pass, Fastrack, and I-PASS. Advanced systems on many US highways do not even require the vehicles to slow down when passing through such checkpoints.

Although for Class III applications a number of solutions are already in place, there are few solutions available for the other two classes. In some cases Class II applications have resorted to using expensive Class III solutions (e.g., JFK airport parking payment lanes offer an option for using E-Z Pass). *This paper presents a first vehicle-to-infrastructure (V2I) pairing system targeting Class I and Class II applications by achieving design goals of low-cost and high-accuracy.*

Low cost and limited instrumentation of the infrastructure are the desired criteria for the Class I and Class II applications. The existing solutions for Class III applications such as E-Z Pass, Fastrack and I-PASS are not readily usable by the other two classes of applications due to the following limitations. (1) For performing an electronic transaction or authenticating by reading a tag's identity, the system needs access to a database holding the association information with users identity and banking information. (2) The vehicle needs to have a device or sticker placed near the windshield or dashboard. Such placements are prone to mounting errors [2] and the involvement of an additional device at the user end limits its flexibility, since deployment is a custom effort and upgrading the hardware is cumbersome. (3) Due to the transmission range of the tags, in scenarios with narrow lanes the signal can be picked up by multiple tollbooths.

Although knowledge of location obtained from the GPS on our smartphone can be used to address the challenges, its accuracy ranges from a few meters to tens of meters [4]. Optical Character Recognition (OCR) based number plate recognition systems can be used to detect and identify a particular vehicle. But such a technique requires a dedicated IR capable expensive camera [1] aiming for a number plate.

The necessity of additional hardware can be addressed by developing the smartness as part of a smartphone based application. But the challenge in performing interactions using a longer range WiFi (or similar) technology is the *accurate identification* of the specific device to pair with, from a large number of in-range devices. In par-

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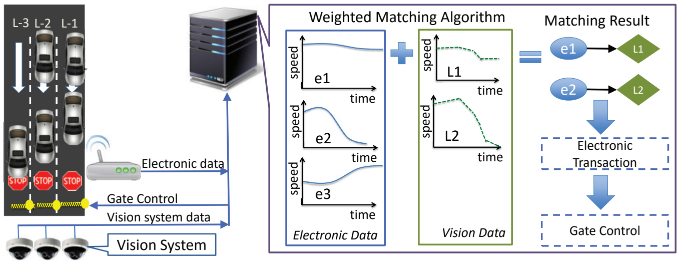

Figure 1: *Soft-Swipe architecture*

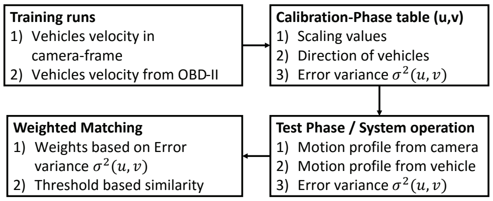

Figure 2: *Soft-Swipe pipeline*

ticular, financial transactions are *location-aimed* in order to charge the vehicle in a particular lane and position for the provided services. In this paper we exploit a distinct property of Class I and Class II applications: *slow and time-varying speed of the vehicles*. We refer to the recent time series of velocities of a vehicle as its *motion profile* or *motion signature*. Our solution uses self-generated natural signatures (specifically, motion signatures) reported by the target object matched with the same signature detected by simple instrumentation of the environment (a video camera) to identify a specific vehicle at a given location (e.g., vehicle A is in lane-4 and next to gate). Our system is comprised of two components: (i) A smartphone connected to the vehicle system using a Bluetooth link or an OBD-II; (ii) A camera which might be already deployed for security purposes. Essentially, Soft-Swipe matches motion-profiles from these two components to match vehicles to respective lanes.

2. SYSTEM OVERVIEW

Soft-Swipe enables V2I based identification of vehicles entering into a multi-lane service station. This is performed by matching motion signatures generated from two types of sources. First, Soft-Swipe needs a signature from the vehicle being serviced that is tagged with the vehicles' identity. This signature may be generated by a device such as a smartphone by fetching the motion profile from the vehicle's OBD-II port. Next, Soft-Swipe needs signatures for the same vehicle generated by external, *location-aimed* devices, that is, devices that are targeted at the locus of interaction, such as a video camera whose field of view covers the multi-lane service station. Note that these signatures are not tagged with the vehicle's identity. For external *location-aimed* sensing, cameras, ultra-sonic range sensors, passive infrared sensors, and RSSI from mobile phones can be used.

Figure 1 depicts the architecture of Soft-Swipe where the internal signature is generated by a service device in the vehicle. A smartphone based transaction can be initiated by a user device with Soft-Swipe -app. After the digital handshake between a Soft-Swipe -app and Access point (AP), the external, location-aimed signatures are sensed from a video camera aimed at the service lane. Soft-Swipe uses these two types of signatures (internal and external) in two important ways as shown in Figure 2. First, during system initialization, these signatures are used to *calibrate* the external sensing components. This allows the camera to estimate velocity of the vehicle based on its motion in the camera frame. During calibration, the accuracy of velocity estimation can be studied to construct a velocity estimation error variance tables. When the system is in operation, the detected motion signature thus obtained is sent to a centralized server-side signature matching module. Here, the external motion signatures are matched to the internal motion signature that contains the identity of the object by assigning appropriate weights to observed matching profile (proportional to inverse of variance). When proper matching occurs, Soft-Swipe can identify the moving object in the sensing field of view, and by definition in the systems proximal locus of interaction.

3. IMPLEMENTATION

Our vision system is implemented in C++ using open source computer vision libraries (OpenCV) which captures a real-time video feed. It finds good features in the frame that can be used to track a vehicle (described by Shi et al. [5]). These features typically include corners, boundaries of a vehicle, etc. Once these features are extracted, the vision system checks how these features have moved across consecutive frames in order to measure their shifts. These shifts are observed in terms of pixels per unit time and referred to as *optical flow vectors* in the computer vision literature [3]. Next, a noise-filter is created to filter out the optical flow vectors that are below a threshold and not in the directions of vehicular movements. The optical flow vectors from different feature points on the vehicle are aggregated to obtain the vehicle's velocity in the camera plane. Later the camera plane velocities are converted to vehicle velocities using the scaling values obtained during calibration phase.

The vision system was implemented using a Logitech Quickcam pro camera and was mounted 2m over the ground level. Additionally, we have experimented with Belkin NetCam HD+ and other off-the-shelf digital cameras. Motion profiles from vehicles are collected by connecting a smart-device with the OBD-II system. Soft-Swipe deployed in a central server (laptop) receives the motion profiles from the vision-system and smart-devices deployed in vehicles (received using Wi-Fi based communication) and are processed. The weighted matching is implemented in Matlab where the motion-profiles from camera and vehicles are matched. The above implementation uses commodity sensors with an average cost of 100 USD/lane. Large-scale production of the system might cost much lower than presented costs.

4. ACKNOWLEDGMENTS

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