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Vehicle engine classification using normalized tone-pitch indexing and neural computing on short remote vibration sensing data☆

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ABSTRACT

As a non-invasive and remote sensor, a Laser Doppler Vibrometer (LDV) has found a broad spectrum of applications. It is a remote, non-line-of-sight sensor to detect threats more reliably and provide increased security protection, which is of utmost importance to military and law enforcement applications. However, the use of the LDV in situation surveillance, especially in vehicle classification, lacks systematic investigations as to its phenomenological and statistical properties. In this work, we aim to identify vehicles by their engine types within a very short period of time to yield a practical expert and intelligent system to classify vehicle engines remotely using laser sensors. Based on our preliminary success on the use of tone-pitch indexes (TPI) over these data, a new normalized tone-pitch indexing (nTPI) scheme is developed to capture engine periodic vibrations by various engine types with vibration data over a much shorter period (from 1.25 to 0.2 s), which makes it possible to monitor slowly moving vehicles around 15 miles per hour. We also exploit the learning power of neural computing, including artificial neural network (ANN), Deep Belief nets (DBN), Stacked Auto-Encoder (SAE), and Convolutional Neural Networks (CNN). To apply a CNN, a two-dimensional array is formulated by stacking nTPI data in an overlapping manner, which is termed as 2DonTPI. The classification results using the proposed nTPI and 2DonTPI over a standard LDV dataset are promising: with encoding duration significantly smaller than that required by the original TPI, consistently high performance is attained for all four neural computing methods. The new vibration data representation combined with neural computing approaches gives rise to a *powerful expert and intelligent system* for vehicle engine classification, which can find a great array of applications for civil, law enforcement, and military agencies for Intelligence, Surveillance and Reconnaissance purposes that are of crucial importance to national and international security.

1. Introduction

THE use of Laser Doppler Vibrometer (LDV) as an important remote sensing instrument has been consistently growing in recent years due to the unique advantages it can provide. An LDV sensor is an active sensor based on sending and receiving laser beam signals: it works by first sending out a laser beam *b* to a targeted reflective surface *S*; if *S* is adequately smooth and retro-reflective, *b* is then reflected back by *S* and received by the LDV as *b'*. The spatial and spectral properties of *the surface's* vibrations can thus be extracted from the time difference and Doppler shift of the received *b'* from the out-going *b*. LDV sensors provide many advantages:

1. Non-invasive measurements: No mass or pressure is applied during the LDV measurement process, and the laser in our LDV is eye-safe: only some high-power types may cause damage to human eyes if viewed directly for a significant time. As an example, LDV exerts no additional pain in non-invasive medical applications such as body temperature and pulse monitoring during medical operations. By contrast, the small dose of radiation from CT or X-ray in medical applications can damage human cells; even the supposedly safer ultra-sound needs long time contact and special jellies that are inapplicable for skin burns or delicate vital sign measurements of organs during surgeries. Additionally, LDV causes no extra damage in non-intrusive civil engineering applications such as inspections of bridges, railways and buildings (Kubota, 2007; Willemann, Castellini, Revel, & Tomasini, 2004) whereas in typical ultrasonic tests water penetration and/or corrosion induce problem-

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atic side effects. Lastly, LDV has been used for delicate inspections of murals and antique fresco paintings in museums where LDV is the only viable means of inspection (Castellini, Paone, & Tomasini, 1996).

2. High spatial and spectral resolution: the expansive and wide range of amplitudes and frequencies offered by LDV sensors give researchers and developers valuable information in both spatial and frequency domains for intensive analysis, classification and clustering. For instance, the sampling rate for a typical LDV is up to 100 KHz whereas the measurable vibrations can be as short as less than five nanometers to several micrometers. The velocity and acceleration evaluated from these sensors are of desirable quality in space and frequency domains from microscopy analysis in biomedical, biological, and medical studies for remote situation surveillance and structural inspections. In Watson, Rhoads, and Adams (2013), the LDV was effectively employed to remotely detect bombs using actively controlled signals, e.g., chirp sounds. The surface vibrations of the suspected objects in response to the well-controlled sound are collected by the LDV situated at a safe distance, as far as 100 m, and the rich spatial and spectral contents are then analyzed to determine if the object is indeed a bomb; the initial results reported are promising. This safe method of bomb detection can replace the robots or dogs currently used by police or other security agencies, and are far more cost effective.

1.1. *Use of LDV in intelligent vehicle classification*

The use of LDV in many research and development subjects has become increasingly more popular due precisely to the foregoing advantages. As a non-invasive and remote sensor with the afore-mentioned benefits, LDV measured data are an ideal modality/phenomenology to detect potential threats more reliably and provide increased protection to society, which is of utmost importance to military and law enforcement institutions. Our task in this work is to identify the engine type of a vehicle from the vibration signals measured by an LDV sensor, *invariant to various nuisance conditions*: from any part of the vehicle, for any environment including weather, under any operating actions, and in as small of a period as possible. However, systematic investigations of LDV behavioral properties and effective exploitation techniques are still needed before LDV can be deployed in the field. Since summer 2014, the three authors from the City College of New York (CCNY) have been collaborating closely with the Sensor Directorate of the Air Force Research Laboratory (AFRL) at Wright Patterson Air Force Base to tackle this problem.

In Wei, Vongsy, Mendoza-Schrock, and Liu (2014), based on the 2014 collaborations between CCNY and AFRL, Wei and colleagues developed a new vibration tone-pitch index (TPI) to represent different vehicle engines, a feedforward artificial Neural Network was then trained to assign classification labels. This work was based on a data set, referred to as *summer-14* “standard” dataset, collected during summer 2014 over 12 different vehicles, which includes multiple modalities amidst vehicles of different types over five weeks. Many vehicles were collected more than once on different time/days and some vehicles share the same make and year differing only in serial numbers. Our measuring procedure proceeds as follows: The LDV sensor is maneuvered around the vehicle being measured to take 24 to 31 points, including the front bumper, above the front wheels, the front and back doors on both driver and passenger sides, and the back bumper. For each point, the driver was asked to exert five different operating states: *idle, sweep (idle to 3000 RPM), engage drive, 2000 RPM*, and *power on the AC*. For each state, the LDV recorded a 30 s time sequence. To ensure adequate data quality: (1) a retro-reflective tape was posted

Fig. 1. The four types of vehicle engines present in the summer-14 dataset.

on the vehicles’ surface for points where the LDV collected data; (2) The distance from the LDV sensor to the collection point was set at approximately ten feet; (3) Sound noise was required to be at a minimum during the 30 s collection period. In total, there are four different types of engines involved in this data set: I4 (sedan), 11 L Diesel I6 (1-axle truck), 15.2 L diesel I6 (2-axle truck), and V6 (sedan), as illustrated in Fig. 1.

Based on this summer-14 dataset and the ensuing intensive analysis, the inherent features of LDV data from multiple vehicles are first studied, especially their main difference from human speech signals. The TPI scheme is then developed to capture the engine’s periodic vibrations and the associated fundamental frequencies of the vehicles’ surfaces. After extensively administering and exploring more than 10 different well-established classifiers, we discovered that a feedforward artificial neural network with 20 hidden neurons can deliver the optimal performance to classify vehicles’ engines based on the spectral tone-pitch indexes in both the cross-validation and the intensive test method. The classification results using the proposed approach over the complete LDV dataset collected by our team are exceedingly encouraging; consistently higher than 96% accuracies are attained for all four types of vehicle engines.

1.2. *Problems of TPI in practical use*

Despite its initial success in delivering desirable classification performances, one of the major obstacles in the way of practical use is the relatively long duration of the signal window demanded by TPI: 1.25 s, that is, for this indexing and classification approach to work, the basic encoding unit must be longer than 1 s, otherwise the classification performance drops considerably from 96% to below 80%. This 1.25 s demand turns out to be a major problem for practical use of this new methodology: if the vehicle is in motion, it is impossible for an LDV to collect reliable signals from a surface for that long.

As reported in Wei, Liu, Zhu, Mendoza-Shrock, and Vongsy (2015) we made an effort to use TPI to classify vehicles in motion. However, to ensure the 1.25 s duration demanded by this approach, the vehicle must move extremely slowly: for any vehicle, the surface that can be reliably measured is less than 4 m (generally the distance covered by the front and back doors), the 1.25 s signal duration requires that the vehicle cannot move faster than 2.8 miles/h (MPH). Furthermore, to achieve reliable classification and combat noise effects, the encoding signal should be longer than 1.25 s to allow for a majority voting scheme (to be detailed in the next section). Thus, the vehicles need to move even slower, making the TPI based moving vehicle classification entirely impractical. One possible alternative is to focus the laser beam of an LDV on the front or back plate or bumper, however this strategy fares no better: based on our experiments, with our LDV, if the