An approach to improving sound-based vehicle speed estimation

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Abstract—We consider improving the performance of a recently proposed single-sensor acoustic vehicle speed estimation method. In the original method, an intermediate feature, referred to as the analytical speed-dependent feature, was proposed for both vehicle detection and speed estimation. The MA feature maximizes at the instant of the vehicle’s closest point of approach, which represents a training label extracted from video recording of the vehicle’s pass by. In this paper, we show that the original labeling approach is suboptimal and propose a method for label correction. The method is tested on the VS10 dataset, which contains 304 audio-video recordings of ten different vehicles. The results show that the proposed label correction method reduces average speed estimation error from 7.39 km/h to 6.92 km/h. If the speed is discretized into 10 km/h classes, the accuracy of correct class prediction is improved from 53.2% to 53.8%, whereas when tolerance of one class offset is allowed, accuracy is improved from 93.4% to 94.3%.

Index Terms—deep neural network, log-mel spectrogram, noisy labels, traffic monitoring, classification

I. INTRODUCTION

Traffic analysis and planning represent indispensable parts of an intelligent transportation system. Large volumes of traffic data enable significant improvements in the performance of transportation, traffic safety and automatic traffic monitoring (TM) [1]. The TM data are used for various applications, such as traffic flow analysis [7], traffic congestion detection [8], speed estimation [9], type detection [10], [11], plate number [12] and may be used to predict road accidents [13], [14].

Diverse sensing technologies are utilized in modern TM systems. Some of them involve induction loops, piezoelectric and magnetic sensors, ground and aerial cameras, acoustic sensors, Doppler radar and LIDAR [1]. A study conducted in [15] describes recent advances in computer vision applied in multi-camera vehicle tracking and identification, as well as traffic anomaly detection. TM based solely on vision data is often not sufficient due to sensitivity of image sensors to adverse weather conditions, lighting changes, vehicle headlights and shadows [1], [14], [16], [17].

Advantages of the acoustic-based TM over the other technologies include low price, low energy consumption and low storage space required. Acoustic sensors are easier to install and maintain and are not affected by visual occlusions and lighting variations. They are also less disturbing to drivers’ behavior and have fewer privacy issues [1], [18]. Current acoustic TM methods, described in [7], can be divided into single-microphone [19]–[26] and microphone-array approaches [27]–[29].

One of important concerns in machine learning and deep learning applications for acoustic vehicle detection and speed estimation is the lack of high-quantity and high-quality annotated data [21], [22], [24]–[26], [29]. Furthermore, deep neural networks tend to overfit to corrupted labels, which results in poor generalization on the test dataset [30]. This is why robust training, in the presence of noisy labels, is an important task in supervised learning applications [31].

In this paper, we consider improving the accuracy of single-sensor acoustic vehicle detection and speed estimation, proposed in [7]. The original method introduced an analytical speed-dependent feature, referred to as the modified attenuation (MA), which maximizes at the instant of the vehicle’s closest point of approach (CPA). The CPA instant is represented by a training label manually extracted from video recording of the vehicle’s pass by. This labeling procedure is not optimal due to inconsistent camera view angles at installation sites. Time offset, caused by suboptimal labeling approach, is referred to as the labeling noise. This paper addresses label correction aimed to improve the accuracy of vehicle speed estimation. To that end, we propose to shift the ground-truth CPA instants by amount obtained from the test phase of the MA prediction. This approach yields notable speed estimation accuracy improvement.

We first overview the original speed estimation approach in Section II and then propose label correction method in Section III. Experimental results are given in Section IV and conclusions are drawn in Section V.

II. SPEED ESTIMATION

A. Data

Audio recordings dataset from [7], referred to as VS10, is used to train and test the speed estimation method. Recordings were captured with a GoPro Hero5 Session camera and divided into 304 single-vehicle and 71 environmental-noise audio-video files. Ten different vehicles are included, as reported in Table I in [7]. Vehicles’ speeds range from 30 km/h to
105 km/h. Audio data are extracted from video recordings. Audio files are clipped to 10 seconds with 44100 Hz sampling rate and saved in WAV format with 32-bit float PCM. Dataset labels contain the vehicle’s speed and its pass-by time (CPA instant). The pass-by instant is obtained manually by identifying the time frame of a vehicle starting to exit the camera view.

B. Acoustic features

In this paper, we use modified attenuation, originally proposed in [7] for both vehicle detection and speed estimation. The MA feature represents a modification of the amplitude attenuation factor of the sound signal [20].

The MA feature is defined as follows:

\[ \eta(t) = \frac{\alpha}{\beta v^2 (t_{\text{CPA}} - t)^2 + d_{\text{CPA}}^2} \]  

where \( v \) denotes the speed of vehicle, \( t \) is time, \( t_{\text{CPA}} \) is the CPA time instant, and \( d_{\text{CPA}} \) denotes the vehicle distance at CPA. Vertical and horizontal extents of \( \eta(t) \) are adjusted by \( \alpha \) and \( \beta \), respectively. Appropriate settings of \( \alpha \) and \( \beta \) are outlined in Section II-D.

MA is predicted in a supervised fashion from the log-mel spectrogram (LMS) of input audio. LMS represents a very popular feature in acoustic classification applications [32] and it proved very reliable in vehicle detection and speed estimation [3], [4], [8].

C. Method

The vehicle speed estimation method is introduced in [7] and outlined in Fig. 1. In the first step, input audio signal is transformed to its short-time power spectrum representation, namely LMS. LMS remaps original audio frequencies to their logarithmic mel scale. Next, the MA feature regression is performed using a fully-connected deep neural network (DNN). One example of MA prediction is presented in Fig. 2. The second step comprises speed estimation from the predicted MA. The vehicle’s pass-by time, denoted as \( t_{\text{CPA}} \) and estimated by maximizing the MA profile, is used to detect the vehicle and select an appropriate interval of predicted MA samples for speed estimation. Finally, the speed is estimated using the selected MA samples. As in [7], \( \varepsilon \)-support vector regression (\( \varepsilon \)-SVR) [33] is used in speed estimation due to relatively small size of the dataset.

D. Implementation details

1) Features for MA regression: Original audio signals are clipped to 10 seconds with the sampling rate of 44100 Hz. LMS of audio is calculated using the short-time Fourier transform (STFT). STFT is calculated with 4096-sample Hamming window and 1105-sample hop rate, which results in 400 time frames of STFT [34]. For each time frame, \( N_{\text{mel}} = 40 \) mel coefficients are computed, within the frequency interval of [0, 16 kHz].

The MA feature (1) is calculated with \( \alpha = v \), \( \beta = 0.05 \) and \( d_{\text{CPA}} = 1.5 \) m. The MA value, at instant \( t \), is estimated using a window of LMS features comprising \( Q = 25 \) time frames (stride of 3), centered at \( t \). This setting yields \( M = Q \times N_{\text{mel}} = 1000 \) LMS input features. Fully-connected DNN consists of 1000–200–50–10–1 neurons per layer. DNN is implemented using mean squared error loss, ReLU activation (linear activation in the last layer), \( L2 \) kernel regularization with factor \( 10^{-3} \) and 200 training epochs.

2) Speed estimation: Optimal \( \varepsilon \)-SVR parameters, namely \( C = 10 \) and \( \varepsilon = 0.1 \), are obtained by a grid search. A vector of 73 adjacent MA coefficients, centered at \( t_{\text{CPA}} \), represents input features of the \( \varepsilon \)-SVR block.

The speed estimation model is evaluated with 10-fold cross-validation. Nine folds (vehicles) are used in training and validation, while the remaining fold is put aside for testing. Training and validation datasets are split in a 80%-20% fashion, as described in Section II-B in [7]. The training procedure is repeated 20 times and the results are averaged.

III. NOISY LABELS CORRECTION

Precise prediction of \( t_{\text{CPA}} \) is of pivotal importance for accurate speed estimation. As mentioned in Section II-C, \( t_{\text{CPA}} \) is estimated by maximizing the predicted MA feature. The vehicle’s speed is then estimated from a window of MA samples centered at \( t_{\text{CPA}} \) (see Section II-D2).

The VS10 recordings, described in Section II-A, were captured with a camera installed at the side of a local road close to Podgorica, Montenegro (see Fig. 1 in [7]). Both incoming directions are present in the dataset. Camera positions and

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**Fig. 1.** Block diagram of the speed estimation method.

**Fig. 2.** Top: Original audio signal of vehicle’s pass-by (speed 80 km/h). Middle: Log-mel spectrogram of audio signal. Bottom: True and estimated MA features.
view angles differ slightly for each recording. Various angles of the camera view, with respect to the vehicle’s trajectory, lead to imprecise $t_{CPA}$ labels in the dataset. The predicted MA profiles (testing phase) are shifted with respect to the ground-truth ones by $\Delta_{t_{CPA}}$, as depicted in Fig. 3 (top). This notable shift between the ground-truth and the predicted MA values motivated us to correct the $t_{CPA}$ labels by taking into account the resulting MA predictions on the test dataset.

Generalization of the proposed MA regression is degraded due to imprecise $t_{CPA}$ labeling. Since the true $t_{CPA}$ value cannot be determined precisely by analyzing the video-recording (camera view angle is not known), we propose to correct the ground-truth $t_{CPA}$ by using the predicted MA profiles of the test data. More precisely, for each audio file, the corrected $t_{CPA}$ is calculated as a median $t_{CPA}$ over 20 runs of the proposed MA regression model. For the $t_{CPA}$ correction, we consider only the test results of MA regression. Since the test data correspond to a vehicle not included in the training phase, the regression model does not overfit to the test data. After the labels are corrected, the model is trained again. Improvements in $t_{CPA}$ predictions, due to the proposed label correction, are depicted in Fig. 3 (bottom). Speed estimation improvements are presented in Section IV.

**IV. EXPERIMENTS AND RESULTS**

The proposed method is evaluated in terms of vehicle detection and vehicle speed estimation accuracy. Since vehicle detection is defined as estimation of the $t_{CPA}$ instant, we calculate detection error as a difference between the true and the estimated MA maxima positions. Distribution (histogram) of MA maxima detection offsets of the test data are presented in Fig. 4 (top). The histogram comprises the test results from 20 DNN training iterations. If the error is modeled as a normal random variable, its mean value and standard deviation are improved with respect to [7], from $-0.016$ to $0.009$ and from $0.065$ to $0.053$, respectively. In Fig. 4 (bottom), we compared histograms of the MA maxima values in two scenarios, with vehicle (blue histogram) and without vehicle (orange histogram) passing by the microphone. The width of the green rectangle area, which separates the vehicle and no-vehicle cases, increased from 0.30, obtained in [7], to 0.45. This area represents the optimal range to set the MA magnitude threshold for accurate vehicle detection.

Speed estimation accuracy is evaluated using root-mean-square error (RMSE)

$$ \text{RMSE} = \sqrt{\frac{1}{L} \sum_{l=1}^{L} (v_{l}^{est} - v_{l}^{true})^2}, \quad (2) $$

with $v_{l}^{est}$ and $v_{l}^{true}$ representing the estimated and true speeds of the $l$-th measurement, respectively, whereas $L$ is the total number of speed measurements. Average RMSE values, presented in Table I, demonstrate the effect of $t_{CPA}$ label correction in the training dataset. Compared with [7], the total average RMSE value decreases from 7.39 km/h to 6.92 km/h. Vehicle-by-vehicle RMSE comparison with Table II in [7] shows performance improvement for each vehicle except for Opel Insignia, where RMSE is slightly increased.

Speed estimation accuracy is also evaluated in a classification framework. Namely, vehicle speeds are divided into 8 classes, starting from 25 km/h, with a step of 10 km/h. Speed classification results are presented in Table II, with $\Delta$ denoting the distance from the true class. The presented results
show improvements of average speed classification accuracies in the cases of $\Delta = 0$ (true and predicted classes coincide) and $|\Delta| \leq 1$ (true and predicted classes are adjacent ones) from 53.2% to 53.8% and from 93.4% to 94.3%, respectively. Note that the presented speed classification results of Renault Scenic and Mazda 3 Skyactive are highly affected by a background environmental noise during dataset acquisition. On the other hand, Opel Insignia outperforms the other vehicles with the outstanding $|\Delta| \leq 1$ accuracy of 100.0%.

V. Conclusion

In the paper, we considered how the test results of intermediate MA feature regression could be used to improve coarse labels, obtained by visual scene inspection. The proposed label correction method improved the average speed estimation error by 0.47 km/h. When formulated as a classification problem, with the discretization interval of 10 km/h, the achieved accuracy improved 0.6% for correct class prediction and 0.9% in the case when one class offset is allowed.

Our future vehicle speed estimation research will focus on data-oriented approaches such as data augmentation and extending the dataset with additional vehicles.

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**Table II**

| Vehicle | $\Delta = 0$ | $|\Delta| = 1$ | $|\Delta| = 2$ | $|\Delta| > 2$ | $|\Delta| \\ in T$ |
|---------|--------------|----------------|---------------|--------------|----------------|
| Citroen C4 Picasso | 62.6% | 28.9% | 8.5% | 0.0% | 91.5% |
| Mazda 3 Skyactive | 43.9% | 48.3% | 6.2% | 1.6% | 92.2% |
| Mercedes AMG 550 | 50.2% | 48.5% | 1.3% | 0.0% | 98.7% |
| Peugeot 407 | 42.4% | 52.2% | 2.4% | 0.0% | 97.6% |
| Opel Insignia | 69.8% | 30.2% | 0.0% | 0.0% | 100.0% |
| Peugeot 3008 | 62.2% | 31.0% | 6.0% | 0.2% | 93.5% |
| Renault Captur | 61.7% | 33.3% | 5.0% | 0.0% | 95.0% |
| Renault Scenic | 44.9% | 42.3% | 8.7% | 4.1% | 87.1% |
| VW Passat B7 | 52.0% | 45.4% | 2.6% | 0.0% | 91.4% |
| Average | 58.8% | 40.5% | 5.0% | 0.7% | 94.3% |
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