Speed changes classification based on automotive spectrogram data analysis

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Abstract. Spectrogram is a very useful sound representation, showing frequency contents as a function of time. However, the spectrogram data are very complex, as they may contain both lines or curves corresponding to partials (harmonic or not), whose frequency changes in time, as well as noises of various origin. In this paper, we address the extraction of line parameters from spectrograms for audio data, recorded for cars passing by an audio recorder. These lines represent pitched sounds, and the frequency along these lines is usually related to the vehicle speed. Our goal is to detect whether the vehicle is slowing down, speeding, or maintaining approximately constant speed. However, the lines may be broken, they bent when the car is passing the microphone because of the Doppler effect, which is strongest when very close to the microphone, and they are on the noisy background. Our goal was to elaborate a methodology, which extracts a simple representation of parameters of these lines (possibly broken, curvy and in noise), and allows detecting the behavior of drivers when passing the measurements point, e.g. near the radar. Audio data can be very useful here, as they can be recorded at low visibility. The proposed methodology, together with the results for on-road recorded audio data, are presented in this paper. This methodology can be then applied in works on road safety issues.

Keywords: Speed Changes Detection · Hough transform · Audio signal analysis.

1 Introduction

Road accidents in majority of cases are caused by a failure to yield the right-of-way, or excessive speed, inadequate to the given road conditions. This information is confirmed by numerous, detailed studies on road incidents and their consequences [1–3]. It is also important that the values of vehicle speed, as circumstances of accident, vary in a wide range, from relatively low speeds in urban areas to high speeds on expressways and motorways.

Personal features of a driver and his or her habits affect the reactions in dangerous driving situations [4, 5]. Usually, drivers are classified according to the level of their "aggressiveness" in driving [5–8]. An aggressive driver is characterized by high speeds of driving and numerous and sudden changes of instantaneous speed, which are associated with periods of acceleration and braking.

The higher speed variations, the greater the interactions between the vehicles on the road and the higher the associated danger [9]. Besides aggressive drivers, careful drivers can also be identified. They try to maintain a constant moderate speed and avoid rapid acceleration and braking, which together are indicators of safe behavior. Many drivers are aware of the impact of speed on the road accidents occurrence. However, they believe that road accidents are caused not only by driving too fast but also by driving too slow, which implicates dangerous behavior of other drivers [4, 10].

Economic development is associated with an increase in the number of road transport means. This is followed by the development of infrastructure, and it also requires the introduction of traffic monitoring and control systems. The systems dedicated for speed measurements and vehicle classification contribute to the road safety and traffic fluency. Many transport agencies often use the results of speed tests as the basis of decisions on setting speed limits, traffic signs, synchronizing traffic lights, and assessing their effectiveness [11].

Numerous study works clearly indicate the possibilities of improving traffic safety through comprehensive implementation of traffic management and vehicle speed management systems [12–14]. They can be based on magnetic induction, piezoelectric effect, Doppler effect and computer video analysis techniques.

Traffic measurement technologies can be classified into intrusive and non-intrusive methods [15]. The technologies of the first group basically consist in placing a recorder and a sensor on or in the road:

- Pneumatic road tubes, placed across the road lanes to detect vehicles by means of pressure changes that are generated by a vehicle tyre passing over.
- Piezoelectric sensors: the sensors are placed in a groove along the roadway surface of the lane(s) monitored.
- Inductive loops: the loops are embedded into roadways; they generate a magnetic field [16].

Non-intrusive consist in remote observations:

- Manual counts: trained observers gather traffic data, e.g. vehicle occupancy rate, pedestrians and vehicle classifications.
- Passive and active infra-red sensors: the presence, speed and type of vehicles are detected based on the infrared energy radiating from the detection area.
- Passive magnetic sensors, fixed under or on top of the roadbed.
- Microwave radar: this technology can detect moving vehicles and their speed (Doppler radar) [17].
- Ultrasonic and passive acoustic methods: the devices emit sound waves to detect vehicles by measuring the time needed for the signal to return to the device. The passive acoustic sensors are placed alongside the road and can collect vehicle counts, speed and classification data [18].

– Video image detection, gaining popularity recently: video cameras record registration plates, vehicle type and speed [19–21].

These technologies differ in their installation costs; they have advantages and disadvantages [15, 23, 24]. Almost all of them allow measuring vehicle speed, but acceleration measurements are not taken into account. Therefore, the development of such systems is needed.

There are studies on the determination of the speeds of vehicles using acoustic waves generated by passing vehicles [25, 26]. In particular, an acoustic vector sensor and sound intensity measurement techniques are applied in these methods [27]. They utilize sophisticated algorithms for the sound intensity processing in the domain of time and frequency. The obtained results indicate the potential of these methods, and a possibility of using them as a supplementation of currently employed techniques in measurements of vehicles speed and acceleration.

Since it is possible to assess speed changes from audio data, we also follow this approach in the work presented in this paper.

1.1 Audio Data

The audio data we used were recorded on-road in controlled conditions, i.e. on an unfrequented road, to assure that the sound of the recorded car is not accompanied by sounds of other cars. Mc Crypt DR3 Linear PCM Recorder, with two built-in microphones, was used to record stereo audio data, 48 kHz/24 bit. The audio data were recorded in the summer (August 2nd, 2016), winter (January 16th, 2017), and spring (March 31st and April 5th, 2017). Each data item represents a single drive, 10 second long, with the moment of passing the microphone in the center of the recording. Each drive represents one of 3 classes:

– acceleration, 111 drives,
– deceleration, 113 drives, and
– stable speed (with possible small, unintended variations), 94 drives.

A 300 m road segment was used for each drive. Speed changes were performed from about 60 m before to 60 m after passing the audio recorder.

Summer Recordings. Summer recordings were made in Ciecierzyn, Lublin voivodship, in Poland, on a sunny day (weekday), from 10 a.m. to noon. The road was in a broad mild basin, so the cars were not driving uphill nor downhill. The audio recorder was placed 1.5 m above the surface and as close to the road as possible. Three cars were recorded: 2 with Diesel engine (Toyota Corolla Verso and Skoda Octavia), and 1 with gasoline engine (Renault Espace). For each car, two drives per class were recorded, with additional 2 drives of Skoda. The audio data represent acceleration 50–70 km/h, deceleration 70–50 km/h, and stable speed of 50 km/h, plus 2 drives at 70 km/h for Skoda (20 drives altogether).

Winter Recordings. Winter recordings were made in the outskirts of a small town, Lubartów, Lublin voivodship, in Poland, from 6 p.m. to 8.30 p.m. [26]. There was snow on the road, but not on the area below the tires. One car was recorded: Renault Espace IV (2007), with manual transmission. The data represent 84 drives, namely 28 for acceleration 50–70 km/h, 28 for stable speed, 50 km/h, and 28 for deceleration 70–50 km/h, all without changing gear and without applying brakes (engine braking only).

Spring Recordings. Spring recordings were also made at the same road near Lubartów, in 2 days in early spring, from 8.30 a.m. to 11.30 a.m. The weather was windy on March 31st, and good on April 5th. The wind gusts did not affect the audio data, but to avoid strong wind gusts, a windscreen was applied later. The recorded cars included Renault Espace III and Renault Espace IV, both with a gasoline engine, Skoda Octavia with a Diesel engine, and Smart ForFour with a gasoline engine, all with a manual transmission. The data include 214 drives, namely 77 for acceleration (50–70 km/h, and 50–80 km/h for Skoda), 58 for stable speed, at 60 km/h, 70 km/h, and 80 km/h, and 79 for deceleration (80–40 km/h, 80–50 km/h, and 70–40 km/h); brakes were applied here.

2 Methodology

Audio signal can be useful as a source of information about traffic, as it can be recorded at low visibility conditions, but it requires processing to extract this information. In our approach, we use spectrogram, i.e. the graph representing the frequency contents of sound as a function of time, as a basis of a graphic-based approach. Spectrograms are based on FFT (Fast Fourier Transform) spectrum, calculated for 170ms frame, with 57 hop size (i.e. with 2/3 overlap), Hamming-windowed. In the preprocessing step the signal was low-pass filtered, and spectra for frequencies up to 300 Hz were used for preparing spectrograms. To facilitate further work, the audio data for each drive were represented as 4 spectrograms: 5 seconds before passing the microphone for the left channel, 5 s for the right channel, 5 s after passing the microphone for the left channel, and 5 s for the right channel. The linear frequency scale was used in spectrogram.

Spectrograms for automotive data, representing cars passing the road near the microphone, contain lines at low frequencies. These lines are mostly horizontal if the driver maintains approximately stable speed, rising up if the driver is accelerating, and descending if the driver is decelerating. Exemplary spectrograms are shown in the upper left set of images presented in Fig. 1. We selected short segments of sounds, with clearly visible lines. These lines correspond to partials (harmonic or not) of pitched sounds, whose frequencies are usually related to the car speed. These frequencies change in time, and this is illustrated in the spectrogram. However, the spectrogram data are much more complex, as they also contain noises. Additionally, the lines are actually curves, especially at the moment of passing by the microphone. This is caused by the Doppler effect, most pronounced near the microphone.

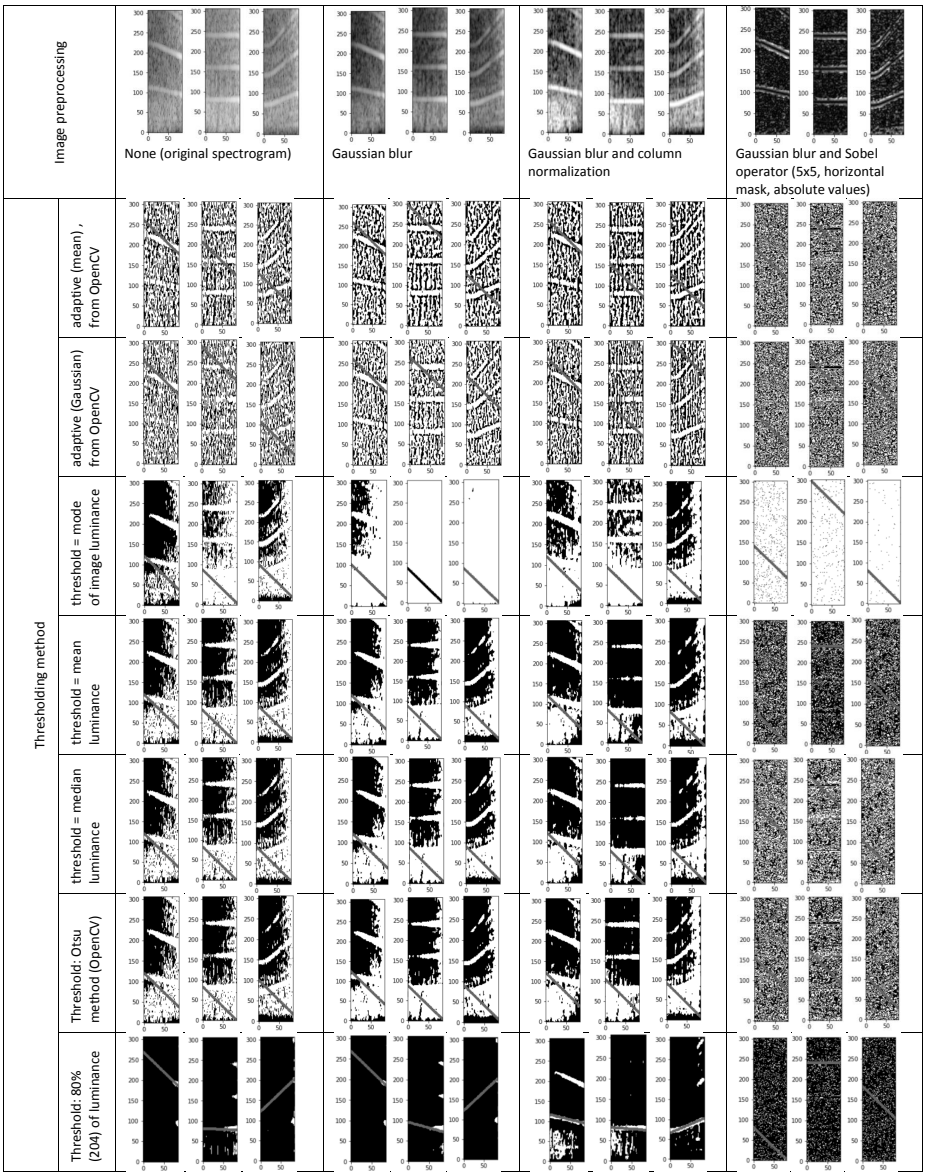

Fig. 1. Hough transform spectrograms in grayscale, for various image processing methods and thresholds. The images in the cells of this table represent spectrograms for deceleration (left), stable speed (center), and acceleration (right). Gray lines on black-and-white images represent the results obtained from the Hough transform, i.e. θ and r corresponding to the strongest line, as indicated by the maximum of the accumulator array

In the presented approach, we aim to extract line parameters from these spectrograms. Our goal is to detect whether the vehicle is accelerating, decelerating, or maintaining approximately stable speed. However, the lines in the spectrogram may be broken, there is a lot of noise in the spectrogram, and the lines bent when the vehicle is passing the microphone. Still, we believe that it is possible to extract parameters of these lines, and then this small set of parameters can represent a very complex spectrogram as indicator of speed changes.

Edge detection in the image can be performed using e.g. Sobel operator. The lines of interest in our spectrograms are either horizontal, or slightly ascending or descending. However, as we can see in the last column of images in Fig. 1, the edges extracted by the Sobel operator do not represent our lines. Therefore, more sophisticated approaches must be elaborated.

We decided to apply Hough transform for line detection [28]. In its main form, the Hough transform takes black-and-white (binary) images as an input. The spectrogram data are in grayscale, and the luminance values represent the energy in the corresponding time-frequency points. Color scales can also be used. Therefore, the use of Hough transform is not so straightforward in our case.

Hough transform for line detection. In the Hough technique, each point in the image indicates its contribution to the physical line. Line segments are expressed using normals: $x\cos(\theta)+y\sin(\theta) = r$, where r is the length of a normal, measured from the origin to this line, and θ is the orientation of r wrt. the x axis. For any point belonging to a given line segment, r and θ are constant. The plot of the possible r, θ values, defined by each point of line segments, represents mapping to curves (sinusoids) in the polar Hough parameter space. The transform is implemented by quantizing the Hough parameter space into accumulator cells, incremented for each point which lies along the curve represented by this r, θ. Resulting peaks in the accumulator array correspond to lines in the image.

For $\theta = 0$ the normal is horizontal, so the corresponding line is vertical. Similarly, $\theta = 90$ corresponds to horizontal line; r is expressed in pixels. Fig. 2 illustrates Hough accumulator matrix (right image), calculated for a grayscale spectrogram (left image), converted to a binary image (center image).

The Hough transform is applied on binary images. There are implementations that take grayscale images as an input, but then the image is transformed to binary. We applied various image processing techniques to obtain binary representations of the spectrograms, as shown in Fig. 1 and Fig. 3. We wanted to determine two approaches for detecting lines in the spectrogram using Hough transform, namely threshold-based grayscale-to-binary conversion as input of the Hough transform (1st approach), and Canny edge detection [30] used as grayscale-to-binary conversion before applying the Hough transform (2nd approach). OpenCV implementation of the Canny algorithm was used [29]. In the preprocessing step, we tested Gaussian blur, column normalization, and Sobel operator in the 1st approach. Sobel operator was not used in the 2nd approach, as it is used as the edge detector operator in Canny algorithm. Gaussian blur was applied to get rid on noise, and column normalization was performed to obtain the same energy levels for each time point, as the energy at the moment

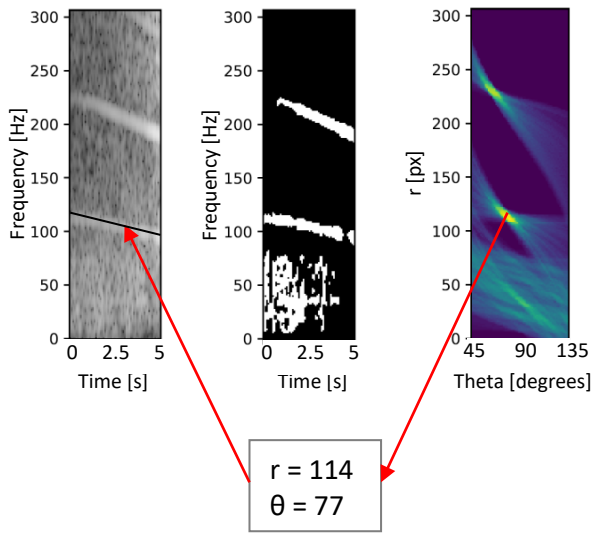

Fig. 2. The spectrogram in grayscale (left), in black-and-white (center), and the accumulator (right) for this spectrogram. The line marked in the left image corresponds to the maximum of the accumulator array

of passing the microphone was much higher than in the remaining parts of the spectrogram. Column normalization consisted in rescaling each column of the spectrogram to the range $\{0, 255\}$, corresponding to 8-bit grayscale.

7 thresholding versions were used next for the 1st approach, and 3 for the 2nd approach. The thresholds tested in the 1st approach included: 80% of luminance, Otsu method, median luminance, mean luminance, mode of the luminance, adaptive (Gaussian) threshold from OpenCV, and adaptive (mean) threshold from OpenCV. Thresholds tested in the Canny algorithm included

- 20% and 80% of luminance,
- 0.66 of the mean luminance and 1.33 of the mean luminance,
- 0.66 of the median luminance value and 1.33 of the median luminance value.

Our goal was to find the preprocessing and thresholding that work best.

The analysis of the results of this processing, shown in Fig. 1 and Fig. 3, indicated which methods can be applied for further work on classification of these data into 3 classes, i.e. acceleration, deceleration, and stable speed. Next, we extracted parameters to represent lines in classification. As a result, we propose the following 2 approaches of extracting spectrogram representations:

1. Gaussian blur of the spectrogram, column normalization, and next threshold 80% of luminance in grayscale-to-binary image conversion are applied. Afterwards, the Hough transform is applied to find white lines in the processed image, for θ between 45 and 135 degrees. A 2D array (accumulator)

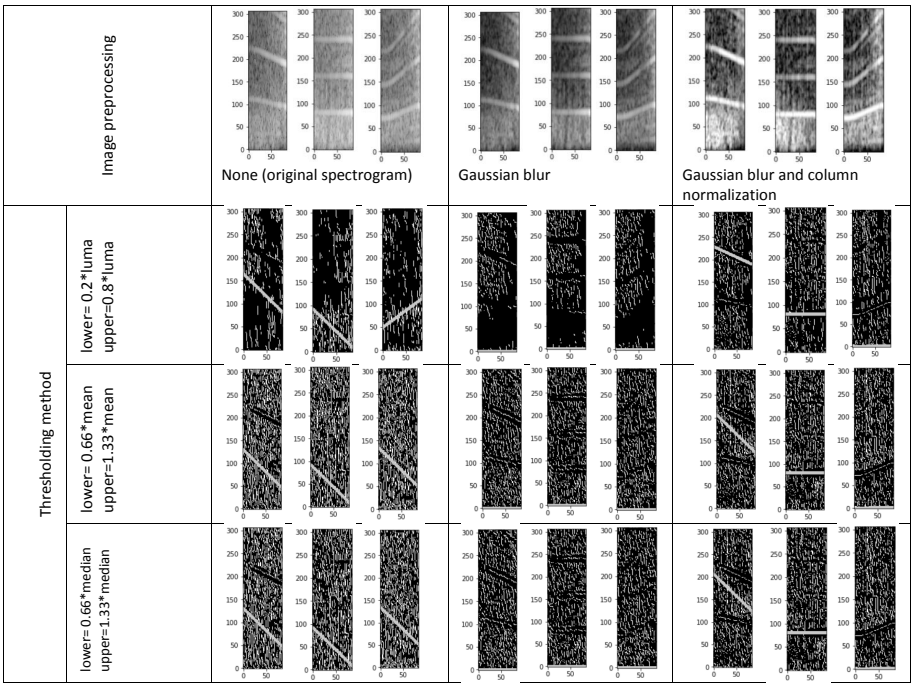

Fig. 3. Hough transform for various spectrograms versions, with Canny edge detector applied for grayscale-to-binary conversion, with various thresholds.

is calculated, and its maximum indicates θ corresponding to the strongest line in the spectrogram. For each of 4 spectrogram parts calculated for a single drive, the maximum of the accumulator and its corresponding θ and r constitute our set of parameters, i.e. 12 parameters represent one drive.

2. Canny edge detection algorithm is used as grayscale-to-binary image conversion method, instead of simple thresholding. Out of 3 tested Canny threshold sets, 20/80% yielded best results (see Fig. 3, so these thresholds were selected. Again, the maximum of the accumulator and its corresponding θ and r for each of 4 spectrogram parts constitute our 12-element feature set.

This way, very simple representations of complex spectrograms can be used, and we applied random forests as classifiers for these data. Representation 1 yielded better results, as shown in the next section.

Since we have such a simple representation, we actually do not need complicated classification algorithms. Even more, we propose 3 simple heuristic Methodologies of classifying the underlying audio data into acceleration, deceleration, and stable speed classes, based on representation 1, as follows.

1. We take θ corresponding to maximum accumulator of the 4 spectrogram parts for this sound. If $\theta > 93$ the data are classified as acceleration, if $\theta < 81$ the data are classified as deceleration, and other values indicate stable speed. The thresholds were experimentally chosen.
2. We take θ corresponding to the greatest r in the feature vector, and apply the same classification rule as in methodology 1 (e.g. 81 and 93 as thresholds).
3. We also used θ and r values corresponding to the maximum of the accumulator to calculate a decision tree, in order to obtain an illustrative and well grounded classification rule.

These methodologies were next tested in this work.

3 Experiments and Results

Random forests were used as classification tools for the proposed spectrogram representations, yielding 85% accuracy for representation 1 and only 66% for representation 2. Tab. 1 illustrates the results obtained for both representations through CV-10 cross-validation.

Fig. 1 also visually shows that the most effective procedure is based on Gaussian blur and normalization for 80% threshold. This is why we decided to use this method in further experiments.

Fig. 3 illustrates how using Canny edge detection method influences the results of Hough transform, when using the results of Canny method as the input of the Hough transform. As we can see, the best results are achieved for the thresholds of 20% and 80% of luminance values, and this is why these thresholds were applied in further experiments.

Table 1. Confusion matrices for the random forest classifiers and a) Hough line parameters from binary image obtained through 80% thresholding (representation 1), b) Hough line parameters detected via Canny edge detection (representation 2).

a)

Classified as:	Dec	St	Acc
Dec	101	8	4
St	12	73	9
Acc	0	14	97

b)

Classified as:	Dec	St	Acc
Dec	71	10	32
St	18	62	14
Acc	27	7	77

The heuristic methodologies proposed in the previous section yielded 77% for Methodology 1, 68% for Methodology 2, and 76.4% for Methodology 3 in CV-10 cross-validation; these results are quite good, as 82.4% was achieved using the tree built for the entire data set, i.e. using Methodology 3. As we can see, our simple heuristic Methodology 1 works as well as a decision tree (Methodology 3). The confusion matrices for these methodologies are shown in Tab. 2 for Methodology 1 and Methodology 2, and in Tab. 3 for Methodology 3. As we can see, acceleration and deceleration are rarely confused. The classification rules obtained via Methodology 3 in the form of the decision tree (built using the whole training set) is shown in Fig. 4.

Table 2. Confusion matrices for the heuristic methodologies (a) 1 and (b) 2 (for Hough line parameters from binary image obtained through uniform thresholding)

a)

Classified as:	Dec	St	Acc
Dec	92	15	6
St	15	65	14
Acc	3	20	88

b)

Classified as:	Dec	St	Acc
Dec	97	13	3
St	19	71	4
Acc	23	41	47

Table 3. Confusion matrices for the J4.8 decision tree classifiers, CV-10 [31]

Classified as:	Dec	St	Acc
Dec	86	19	8
St	17	68	9
Acc	4	18	89

4 Summary

In this paper we aimed at elaborating a methodology of extracting a simple representation automotive spectrograms. Our goal was to extract parameters of lines representing accelerating, decelerating, or maintaining stable speed. These lines are curvy, often broken, and accompanied by noise. Still, we managed to extract line parameters, and obtain a very simple representations, which allows detecting the behavior of drivers when passing the microphone or other measurements point, e.g. the radar. We proposed and tested several methodologies of extracting and representing lines in classification of speed changes.

The recognition accuracy still needs improvement. We plan to inspect thoroughly the misclassified examples, as the misclassification may be caused by distant sounds, interfering with the target sound. Also, to avoid parameterizing curves caused by the Doppler effect and minimize the influence of other sounds, we consider limiting the analyzed sound segments, namely discard the moment of passing the microphone (with strong Doppler effect) and keep the remaining part in which the target sound is loud enough to mask accompanying sound. It is possible that a shorter segment (e.g. 4 seconds, 2 seconds before and 2 seconds after passing, excluding the moment of passing) will work better. However, the exact duration which will work best is to be found in further work.

This work focused on single drives (for single vehicles), but line detection algorithms can also applied when multiple cars are passing at the same time. Therefore, the same methodology can be adopted to the recordings of multiple vehicles and thus multiple lines in future work.

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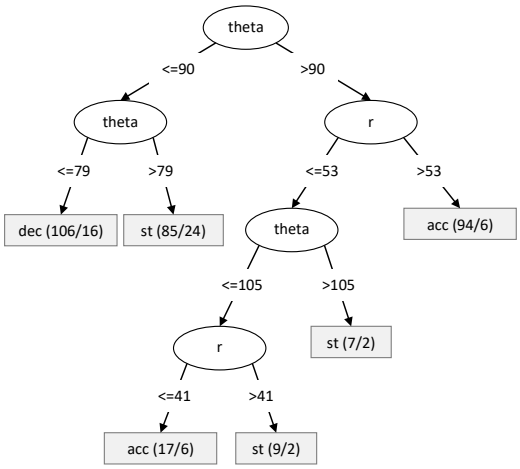

Fig. 4. The decision tree for the 3rd methodology, yielding 82.4% accuracy

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