A machine learning approach for ultrasonic noise classification and suppression

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Zusammenfassung: In this paper we present a novel approach for using industrial grade ultrasonic sensors to perform echolocation by detecting ultrasonic echoes in a noisy environment using machine learning. A 2-step approach is presented starting by signal classification and followed by noise suppression. We show how this methodology is robust against the influence of ultrasonic noise sources in the environment as well as undesired reflections coming from the terrain. Several noise sources and noise powers are assessed as well as different terrain types. The results are bench-marked against the state of art energy thresholding, matched filters correlation algorithms and noise suppression methodologies, clearly showing the superiority of the machine learning based approach.

Schlüsselwörter: machine learning, artificial intelligence, ultrasonic and noise

1 Introduction

Ultrasonic sensors are commonly used in the automotive industry for obstacle detection and environment perception. Ultrasonic-based systems are usually comprised of several sensors distributed around the vehicle. These sensors fire ultrasonic waves and report the time of flight (TOF) between these firings and the respective echo reception to calculate the relative distance between the sensor and the obstacle. The TOF information from several sensors is then processed simultaneously using a form of triangulation to determine the exact position of the obstacle in a two dimensional map centered around the vehicle. This map is then used for several higher-end functionalities such as reporting these distances to the end user, automatic parking and braking on obstacles.

The quality of the ultrasonic signal plays an important role in the ability of the whole system to report correct information to the end user and to perform the higher-level driver assistance functionalities. In real life operation, there are several factors affecting the ability of the system to correctly identify the TOF of the ultrasonic reflected echo such as the presence of ultrasonic noise in the environment, the presence of other vehicles equipped with ultrasonic sensors in the vicinity of the vehicle and ground reflection from uneven terrain in the field of view of the sensor.

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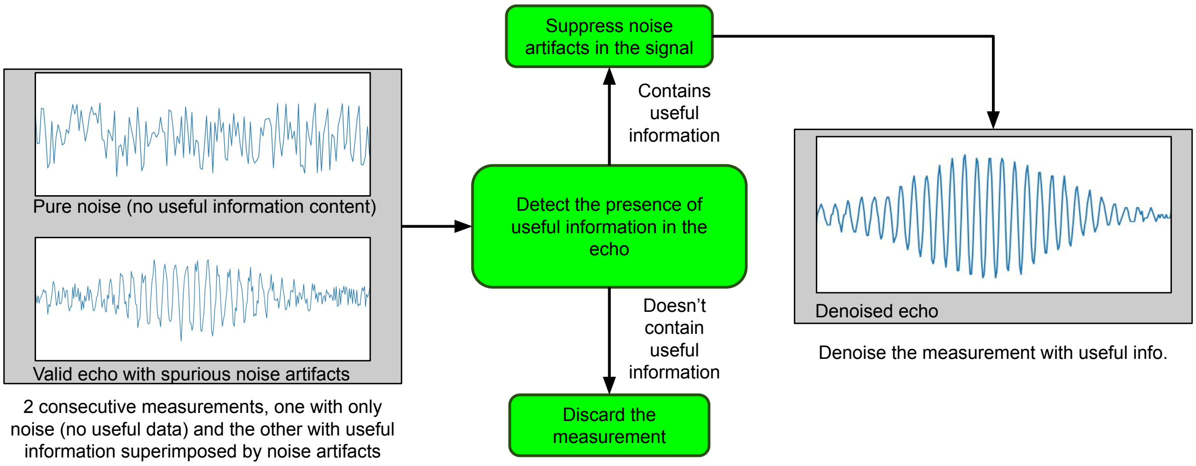

Abbildung 1: The 2-step machine learning based approach of filtering the noise signals with no actual content and further process the valid echoes to suppress spurious noise artifacts

In this work we present a 2-step approach using machine learning to process ultrasonic signals; figure 1. The first step identifies the presence of valid echoes as compared to signals with only noise artifacts [23]. In the second step, the signal with the valid echo is further processed to suppress any spurious disturbance artifacts originating from external noise sources.

2 State of the art

In this section we present a review of the existing methods for noise classification and noise suppression that fit the purpose at hand and also fit the nature of the ultrasonic signal generated by automotive-grade ultrasonic sensors.

2.1 Echo-Noise classification

Ultrasonic sensors are employed in many fields including biomedical imaging, structural integrity analysis and echolocation which will be the focus of this paper. Echolocation is used in different domains such as biomedical devices [1] where ultrasonic sensors is used for echolocation with acoustical feedback for aiding auditory challenged individuals. Robotics is another field where ultrasonic sensors is used for echolocation such as in [2] where ultrasonic sensors are used for robot localization and obstacles detection in the robot vicinity and [3] where ultrasonic sensors are used to detect walls and algorithms are used on top of the echolocation information to estimate the normal distance to the detected walls for more precise localization. Echolocation precision is investigated further in [4] by mitigating the effect of variating temperature on ultrasonic waves propagation speed. In this paper we focus further on the echolocation uses of ultrasonic sensors for automotive industry.

In automotive industry the echolocation functionality of ultrasonic sensors is used for perception of the surrounding environment and this functionality is used by other applications to build advanced driver assistance systems (ADAS). Ultrasonic sensors based

ADAS are used for detection of relevant obstacles [5] and signaling the driver through a human machine interfaces (HMI) with visual or acoustical signals or both. Another use for such systems is to avoid lateral collision [6] through the detection of obstacles in the lateral blind zone of a driver. More advanced ADAS based on ultrasonic sensors perform complete automatic parking maneuvers with the vehicle through the complete awareness of the surrounding environment [7] and [8] whose performance could be validated through methods as the ones presented in [9]

Further improvement of the performance of echolocation using ultrasonic sensors can be achieved by employing artificial intelligence (AI) methodologies and specifically, artificial neural network (ANN) based machine learning (ML) approaches. A general approach not specific to ultrasonic sensors is presented in [10] which discusses the use of ANN for processing sensor signals. The use of ANNs in ultrasonic signals allows for new functionalities and shows improvements in several fields such as in construction [11]. However the focus of this paper is on automotive industry and one of the first usage of ANN in vehicles is [12] which presents one of the early efforts in the direction of autonomous driving using ANNs for image processing based on cameras mounted on the vehicle. ANNs are used with ultrasonic sensors to achieve better distance measurements [13], extract attributes of the detected obstacle such as posture and shape [14], and the classification of obstacles [15] through the fusion between ultrasonic sensors and infrared sensors.

2.2 Noise suppression

In recent years several denoising methodologies are found in commercial products such as noise cancellation headsets. This family of denoising algorithms perform active noise cancellation [16] to counteract spurious signals coming from external sources. They rely on the fact that the SOI is known and coming from a definite source such as an MP3 player. This is not applicable for automotive ultrasonic sensors because the signal is already mixed at the source and it is not known apriori, which artifacts belong to the SOI and which are spurious and should be suppressed. Therefore we have to rely on other methodologies to identify the spurious noise sources, such as assuming the noise artifacts have only a certain range of frequency components or assuming that the SOI follows a specific model and all other signal components that do not fit this model should be suppressed.

Some trivial methods exist in literature where an assumption is made that the noise is present in certain frequency bands and that the useful signal is present in different frequency bands. In these methods simple filtering mechanisms satisfy the requirement of suppressing the unwanted signal components. This assumption doesn't hold in our case because the signal of interest and the noise components spread of intersecting frequency ranges.

Other methods such as adaptive multistage noise suppression filters [17] [18] are more adequate to the problem at hand. Such filters are by nature complex and include a large number of computations in subsequent steps which also lead to increased runtime and failure to satisfy the realtime constraints.

A family of algorithms that require relatively lower processing power and perform denoising over the whole spectrum are discrete wavelet transform (DWT) based methods. The DWT approach described in [19] and [20] achieves good denoising results in terms of suppressing unwanted spurious signals and extracting the SOI. It comes though with the cost that the extracted SOI is distorted, since it is the result of reconstructing the superimposed wavelets passing the designed noise thresholds. This is not suitable for the ultrasonic sensor signal because the SOI is further processed to extract features pertaining to the reflecting obstacle such as height and class of the obstacle which is then fed into the higher layers of the ADAS for end-user functionalities such as braking on obstacles and automatic parking. Thus, the need arises to have a denoising algorithm that achieves similar noise suppressing results while maintaining the integrity of the SOI.

In literature there exist several publications discussing the use of machine learning and specifically deep neural networks for signal processing. Here we are interested in the family of algorithms that deal with the separation of signal components. Some approaches focus on the extraction of a specific SOI and discard the rest while other approaches consider all the signal components to be of interest and separates the different components such as [21] and [22]. There, the voice of the singer and the background music are both of interest and the algorithm tries to separate them without compromising signal integrity. The problem with denoising ultrasonic sensor signals is more in the domain of the former family of algorithms, where we only care about the echo from the obstacle and discard all other signal components.

In the following section we present the proposed 2-step machine learning based approach. An ANN structure is presented as a solution for the first phase of the approach. A deep CNN structure is also presented to perform noise suppression and extract the SOI from an ultrasonic signal mixture containing an echo from an actual obstacle and different types of environment noise in the same spectrum as the echo signal.

3 Proposed machine learning approach

In this section we present the concept behind the 2-step approach for noise classification and suppression. Each step is discussed separately as the connection between them is straight forward where the decision from the first step dictates whether the signal will be further processed or discarded.

3.1 Echo-Noise classification

The ANN employed is a multi layer perceptrone (MLP) composed of 4 layers. MLP architecture is chosen because of its higher execution speed compared to other ANN architectures such as convolution neural networks or recurrent neural networks which makes it suitable for realtime inference operation on microcontrollers used in automotive industry. The input layer is composed of 700 neurons which is equivalent to the number of samples in each snapshot of the digitized ultrasonic analog signal input. The output layer is composed of 2 neurons representing a one-hot approach for representing the 2 states of detected echo and noise respectively. The ANN also includes 2 hidden layers with 500 neurons each. All the layers in the ANN are structured in a dense fully connected manner as presented in Fig. The activation function used is the hyperbolic tangent (tanh) function and statistical gradient descent (SGD) is used as an optimization algorithm. The number of total samples is divided into 80% training, 10% validation and 10% testing.

3.2 Noise suppression

The main concept of the approach is that the whole measurement is fed into the CNN and the denoised signal is completely regenerated at the output layer of the network. The network is trained on noisy signals with different types and levels of noise using supervised learning. The label at the output layer for each training sample is the same version of the input signal but with no noise component and only the echo features are present.

The structure of the network is the classical hour glass shape with the difference being that it is purely convolutional with no dense layers. The network is compressed using downsampling and decompressed using upsampling as described in fig. The number of layers is optimized to be 7 layers and the number of activation maps is set to a maximum of 128 kernels at the most compressed layer located in the middle of the neural network. The hyperbolic tangent (tanh) is used as activation function to limit the maximum values of the firing of the neurons, especially at the output layer where an extreme value could lead to the occurrence of false positives and unexpected behaviour. The output and the input layers are of the same size as the number of samples present in one measurement from the sensor.

4 Measurement campaign and data collection

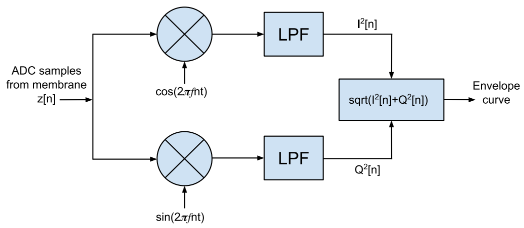

Abbildung 2: Pre-processing after performing data acquisition

The employed data acquisition setup is based on the Valeo ultrasonic sensor adapted with an analog signal interface. The analog signal output is sampled using an analog to digital converter (ADC) and preprocessed before being used. The carrier frequency of the ultrasonic sensor used is 51.2 KHz. The sampling rate at which the signal is sampled is 500 KSample/S which is higher than the nyquist rate of 102.4 KSample/S to avoid loss of information due to sampling. A resolution of 12 bits per sample is used to minimize the effect of the quantization error. The carrier frequency has a predetermined value and contains no information of interest therefore it is removed and the baseband signal is extracted which is also referred to as the envelop signal. In order to obtain the envelop signal, the in-phase and quadrature components are extracted by multiplying the input signal with the carrier frequency and a 90 degree phase shifted version of it respectively. The result is then passed through a low path filter (LPF) to eliminate the double frequency artifacts and isolate the baseband component and then the resulting signals are added to get the overall envelope; fig 2.

The signal samples are then decimated at a number of samples satisfying the condition of being above the nyquist rate of the baseband signal. The signal is further scaled to a range of [0,1] and the scaling factor is applied equally to all the samples at hand. The recorded samples are then divided into 3 groups; training, validation and testing. The extracted key performance indicators (KPIs) are based on the testing set that are never introduced to the ANN in the training phase.

A measurement campaign is carried out that includes several types of obstacles such as tubes, boxes, pedestrians, and objects of non uniform shapes. Measurements are also done under the influence of several noise sources such as truck brakes, clinging keys, air guns and rain.

5 Results and discussion

5.1 Echo-Noise classification

In order to assess the performance of the ML approach to detect echoes under noise conditions we use the F1 score for comparison purposes. The ANN is trained with samples from all the available SNR levels. In figure3 the F1 score of the ML approach and the energy thresholding methodology with raw and correlated inputs at their respective optimum threshold levels are plotted against the same SNR range.

From figure 3 we see that the ML approach gives a superior performance as compared to the energy thresholding approaches especially under low SNR conditions.

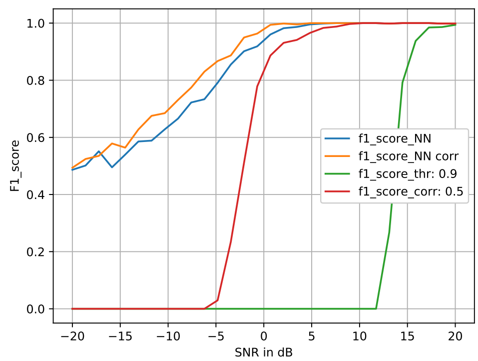

Abbildung 3: Results for echo/noise classification on smooth terrain

The F1 score for the ML approach based on the same artificial neural network structure without the introduction of the different terrain samples in its training set is plotted in figure 4(a) against the optimum threshold levels for the thresholding methodology with both raw and correlated inputs for the gravel terrain.

From figure 4(a) it is evident that the ML approach shows some slight degradation in its capability of detecting the correct echo but remains superior to the thresholding methodology results at the same threshold and after re-tuning to their optimum thresholds under the modified terrain conditions.

From the results we see high dependence of the thresholding approach on the environmental conditions which states the need for re-tuning to the optimum threshold level under each set of conditions. Another approach is to use a universal threshold level but in this case we get a sub-optimum performance under all conditions. The ML approach shows an enhanced performance under different conditions without the need to re-tune the parameters. With prior knowledge of the 2 different terrain types and with the use of a universal optimal threshold for the thresholding method with raw and correlated input, the F1 score results against a dataset including the 2 terrain types are plotted together in figure 4(b).

Not only does figure 4(b) further highlight the superiority of the ML approach to the thresholding approaches but it also emphasizes the importance of augmenting the training set of the ML approach to further improve its capability of correctly detecting echoes in noisy conditions.

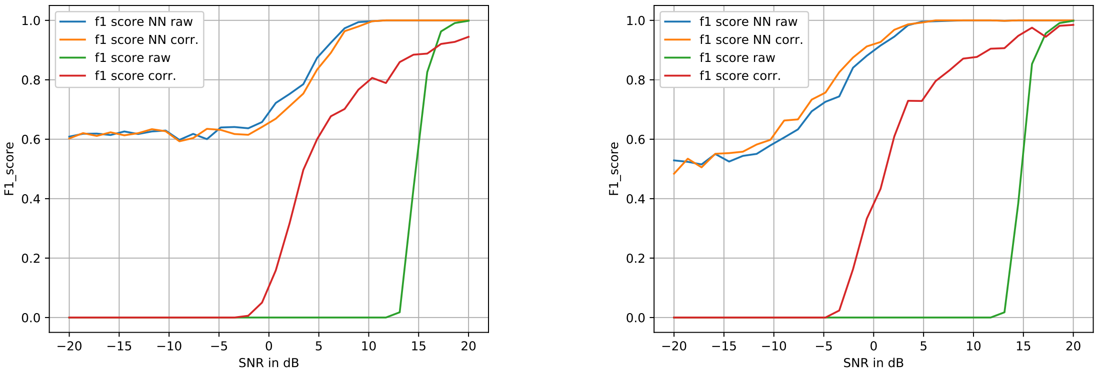

Abbildung 4: Results for echo/noise classification on gravel (ANN trained only for smooth terrain) and mixed terrain types

5.2 Noise suppression

To assess the performance of the ML-based noise suppression phase we bench mark it against the existing DWT noise suppression methodology.

In figure 5(a) we see the performance of both algorithms in terms of suppressing noise presented over a range of SNR values [-5, 20] dB. The DWT performs slightly better in this regard. Nevertheless the main advantage obtained from using the machine learning based approach is that it introduces much less distortion compared to DWT as will be demonstrated.

To adequately judge the performance of the algorithm we take the changes in signal energy not originally present in the SOI as a measure of distortion. This will include added artifacts as well as removed components from the original SOI. This approach will also prevent the trivial solution where the output of the algorithm is an array of zeroes where the noise is completely suppressed but the SOI is also lost. In figure 5(b) we show a comparison between the DWT based method and the machine learning based method in terms of the defined distortion metric. We see that even though the 2 algorithms have comparable performance in terms of noise suppression, the machine learning based approach outperforms the DWT method in terms of conserving the SOI integrity and in terms of the introduced distortions to the original shape of the SOI. We also see that at low SNR levels, the DWT distortion saturates at a ratio of 1.0, indicating that the SOI is completely suppressed and the algorithm is not capable of differentiating between the SOI and the noise components of the signal. In contrast, the machine learning approach is still capable of extracting the SOI from the noisy input signal.

It is important to mention that with further optimization of the hyper parameters of the legacy denoising algorithms we could achieve better results over the available trace set. Consequently the performance could improve but only to a certain limited extent. This is manifested in the trade-off between the noise suppression capability and the distortion introduced to the signal.

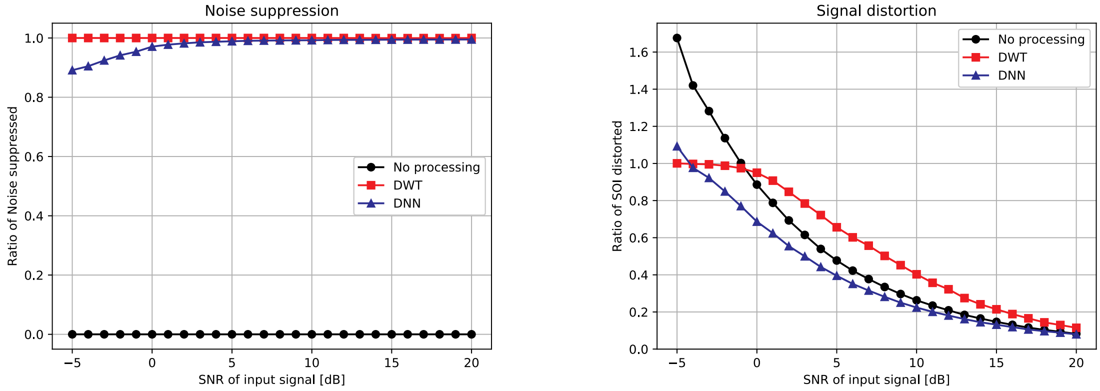

Abbildung 5: Results for noise suppression and distortion introduced by DWT and ML-based denoising algorithms

6 Conclusion

In this paper we presented some challenges facing the use of ultrasonic sensors in automotive industry such as the presence of external sources of noise and the changing terrain types affecting the functionality of the existing echolocation algorithms. To counteract these challenges we presented a 2-step approach for echo/noise classification and noise suppression. This includes MLP and CNN based ANN structures relying on ML techniques to overcome these challenges and provide a method to differentiate between echoes from real obstacles and external noise sources as well as suppressing noise artifacts. Furthermore, this methodology shows increased robustness against changing terrain types. The increase in performance is validated based on results collected from an extensive measurement campaign using recorded ultrasonic echoes from different obstacles as well employing different sources of noise and repeating the measurements of several terrains. The ML-based signal conditioning also proves to to give comparable noise suppression compared to existing algorithms and is superior in terms of the levels of distortion introduced to the SOI.

The superior performance is explained by the fact that the ML based approach learns the typical shape of a SOI as well as the different noise patterns from the numerous measurements used to train the CNN, unlike the DWT algorithm which fits the SOI (the echo in this case) to the base wavelet shape.

By employing the proposed 2-step approach, the noisy measurements are eliminated directly without further processing which saves processing load and runtime. Furthermore, the measurements containing useful information are preserved and the integrity of the SOI is maintained while simultaneously suppressing the unwanted spurious noise artifacts. This leads to higher quality signal information and better functionality for the driver assistance systems relying upon these ultrasonic sensors.

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