World Academy of Science, Engineering and Technology
International Journal of Mechanical and Mechatronics Engineering
Vol:16, No:8, 2022

An Application-Driven Procedure for Optimal Signal Digitization of Automotive-Grade Ultrasonic Sensors

Mohamed Shawki Elamir, Heinrich Gotzig, Raoul Zoellner, Patrick Maeder

Abstract—In this work, a methodology is presented for identifying the optimal digitization parameters for the analog signal of ultrasonic sensors. These digitization parameters are the resolution of the analog to digital conversion and the sampling rate. This is accomplished though the derivation of characteristic curves based on Fano inequality and the calculation of the mutual information content over a given dataset. The mutual information is calculated between the examples in the dataset and the corresponding variation in the feature that needs to be estimated. The optimal parameters are identified in a manner that ensures optimal estimation performance while preventing inefficiency in using unnecessarily powerful analog to digital converters.

Keywords—Analog to digital conversion, digitization, sampling rate, ultrasonic sensors.

I. Introduction

THE signal provided by ultrasonic sensors is analog in nature and needs to be digitized to allow for further processing in the embedded systems of advanced driver assistance systems (ADAS). The digitization parameters such as the resolution of the analog to digital converter (ADC) in terms of bits, and the sampling rate are directly proportional to the cost of the ADC and the rest of the tool chain to be able to cope with the increasing size of the data and to provide processing results in realtime fashion. The higher the ADC's resolution and sample rate, the more precise the digitized signal is, and therefore the less information is lost in the analog signal from the sensor due to digitization. The conflict arises from the fact that the price of the components increases as the ADC capabilities increase, promoting the need to find the optimal digitization values that would allow for the maximum relevant information extraction. The ADAS's capacity to function precisely and dependably is met while maintaining the lowest feasible digitizing parameters and, consequently, the lowest price.

Ultrasonic sensors are used in automotive industry amongst other sensor technologies for environment perception. The functionality of the ultrasonic sensor is based on the calculation of the time-of-flight between transmitting a wave and detecting an echo. This is translated into a radial distance from the membrane of the sensor to an obstacle. Typically, automotive systems that are based on ultrasonic sensors employ several sensors and use the combined data from these sensors to perform triangulation and identify the location of obstacles. Other than the distance, other features can be estimated from the ultrasonic sensor signal such as the height, width, and tilt of an obstacle. These obstacle features provide more information to the ADAS to be able to perform its task effectively.

In the following sections we show how a statistical probabilistic relation is established between the signal generated by the ultrasonic sensor and the obstacle feature being estimated. A systematic method is presented, where the mutual information value is calculated based on the dataset being analyzed. The mutual information is then linked with the Fano [1] inequality identifying the asymptotic maximum performance possible in terms of bit error rate P_{err}. A practical example for obstacle height detection using ultrasonic signals is given on which this methodology is applied.

II. State of the Art

Many recent papers provide strategies for estimating information content, for example [2]. In [3] a proposed method for estimation of mutual information is presented which increases efficiency of the calculations as well as being adaptive in terms of having higher resolution where data are denser. A more specific method to estimate the mutual information using density kernels is presented in [4] The use of mutual information concepts to choose the most relevant features for machine learning is discussed and presented in [5]. This study differs in that mutual information is utilized to analyze the quality of the ensemble signal characteristics as a whole and its dependency on the digitization settings, taking into account all of a given signal's qualities rather than just a part. There are several other publications that discuss different aspects of feature selection using mutual information which differ from the presented approach in this work in the same manner such as [6], [7], [8]. Most of these approaches and more are summed up in [9] also showing the optimal set of features to be selected for an estimation problem based on mutual information analysis. Mutual information concepts applied to ultrasonic signals are present in literature but mainly for medical imaging such as in [10], [11] and [12]. The focus on this work is on the automotive grade ultrasonic sensors.

The asymptotic statistical maximum performance limit was first defined by Fano as early as 1961 in [1]. The concept is further discussed in several recent publications as well such as [13] which investigates the relation between mutual information variations and the corresponding Fano

Mohamed Shawki Elamir is a PhD student in the ”Softwaretechnik für sicherheitskritische Systeme” Department in TU-Ilmenau, Germany (e-mail: mohamed-elamir.mohamed@tu-ilmenau.de).

limit assessment. Some literature also investigated the feature selection from a Fano inequality perspective such as [14]. Using different sources of information increases the mutual information and ability to classify a certain characteristic variation which can be measured by a variation in the Fano limit as discussed in [15] showing the increase in mutual information with sensor fusion techniques and how this reflects on the Fano limit value.

Signals from ultrasonic sensors can be used for obstacle height estimation as presented in [16]. The use of ultrasonic sensors as a source of information for environment perception is also seen in [17] and [18] where the signal from the sensor is further processed for disturbance filtering and noise suppression.

III. Methodology

This work proposes an expression that defines how much knowledge is gained about the feature value X by inspecting the ultrasonic sensor echo signal Y. The more knowledge we gain about the obstacle feature value by inspecting the ultrasonic echo, the more certain is the estimation. This can be defined by calculating its complement, which is the amount of uncertainty about the estimation. In other words, how much uncertainty exists about X by inspecting Y. This fits exactly to the definition of conditional entropy of X given Y. Which is denoted by $H(X|Y)$.

There are two extreme values of the conditional entropy $H(X|Y)$. The first extreme value that the conditional entropy can have is 0. This means that X is perfectly known with complete certainty by inspecting Y. The other extreme value that the conditional entropy could have is $H(X)$, which means that the random processes X and Y are completely independent and there is no information gained about X by inspecting Y. This is also known as the Gibbs's inequality which is represented in (1).

$$H(X|Y) \leq H(X) \tag{1}$$

The value of the conditional entropy between the inspected ultrasonic echo and the value of the feature pertaining to the reflecting obstacle is a measure of uncertainty of the feature with knowledge of the signal. Thus, it is directly related to the amount of error in the feature estimation. The relation between the conditional entropy and the estimation error is derived and proved by Fano [1] and is represented in Fano's inequality in (2).

$$H(P_{err}) + P_{err}Log(|X-1|) \geq H(X|Y) \tag{2}$$

where P_{err} is the probability of error of a binary state random variable having one of two possible values, either erroneous or not erroneous. X and Y are as defined earlier the feature value and the ultrasonic echo resulting from the obstacle having this feature value respectively.

The conditional entropy, which is the uncertainty in the value of X given Y, is further broken down into a relation between the entropy of X and the mutual information between X and Y as in (3)

$$H(X|Y) = H(X) - I(X,Y) \tag{3}$$

Replacing this into the Fano inequalities equation (2) results in a relation between the mutual information between X and Y on one side and the lower bound of the probability of error in the estimation of X given Y on the other side as defined in (4).

$$I(X,Y) \geq H(X) - H(P_{err}) - P_{err}Log(|X-1|) \tag{4}$$

This equation can be physically interpreted that for an estimator to reach a specific level of performance defined by a minimum level of P_{err}, there must be a minimum level of mutual information present between X and Y . This level is identified by the Fano inequality. Moreover, the number of classes plays an important role in the equation and is also taken into account as a variable in this definition. Based on this fact, a wider interpretation is that for an estimator to achieve a certain level of quality for a specific number of classes to be estimated, the mutual information between the estimated feature X and the inspected signal Y must be above a certain value. From this interpretation, we can generate characteristic curves based on Fano inequality, specifying the essential criteria to achieve a certain minimum value of estimation error. These curves will be referred to as Fano characteristic curves and are presented in Fig. 1.

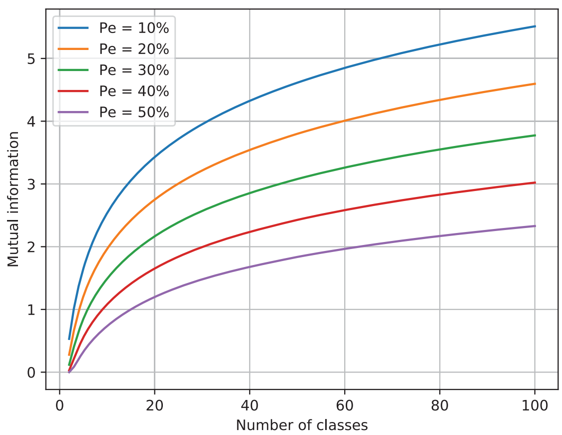

Fig. 1 Fano characteristic curves defining the relation between the mutual information between feature value and the number of classes to be estimated to achieve a certain minimum quality of estimation in terms of probability of estimation error

The mutual information between the change in obstacle feature and the corresponding ultrasonic signal is defined by (5).

$$I(X,\bar{Y}) = \sum_{\forall x}\sum_{\forall \bar{y}}\left(P(x,\bar{y})Log_2\left(\frac{P(x,\bar{y})}{P(x)P(\bar{y})}\right)\right) \tag{5}$$

where, $P(x)$ is the probability distribution function (PDF) of the different height levels of the obstacle. $P(y)$ is the PDF of the different signals in the dataset. The joint PDF between the occurrence that the obstacle has a certain height and the signal generated by the ultrasonic sensor is noted as $P(x, \bar{y})$. Using these curves, and the calculated mutual information value of a predetermined dataset, it is possible to identify the expected performance of an optimal estimator that estimates the value of the specific obstacle feature. By repeating this procedure over a range of possible digitization parameters such as ADC resolution and sampling rate, then the optimal value for the digitization parameters can be identified.

In the next section, a practical example of how this technique is put to use, ultrasonic echo signals from obstacles of various heights are recorded in order to determine the best digitization parameters for this ultrasonic signal, allowing the obstacle height to be determined solely by the inspection of the digitized ultrasonic echo signal.

IV. Practical Application

If the effect of variation of a certain feature such as height of an obstacle can be isolated and extracted from the generated sensor signal, and mapped back to the height value, then with this system, we can have an estimate of the height feature value by inspecting the attributes pertaining to the sensor signal, which in our case is the ultrasonic sensor detected echo. A simple schematic of this system is illustrated in Fig. (2).

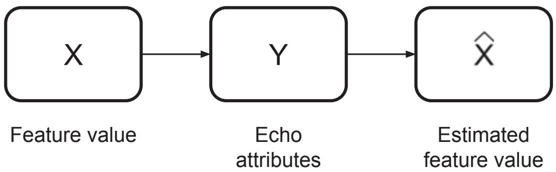

Fig. 2 Schematic representation of the system of obstacle feature value estimation by inspecting sensor signal attributes

A. Measurement Campaign

The measurement campaign is focused on identifying the influence of the variation of the obstacle height on the generated ultrasonic sensor signal. For this purpose a set of Lego cubes are used to build towers of different heights ranging from 2 cm to 50 cm with a 2 cm step.

An automotive grade ultrasonic sensor is used to transmit an ultrasonic wave and detect the echo bouncing off obstacles in the range of the sensor. The signal is collected from the sensor using an analog to digital converter with different values of sampling rate and accuracy. Examples of obstacles with different heights are presented in Fig. (3).

B. Results and Discussion

By decreasing the ADC resolution we see that the mutual information between the obstacle height value and the corresponding ultrasonic signals in the dataset is decreasing as shown in Fig. (4). For the highest 5 values of the ADC resolution, namely [8, 10], we see no change in the mutual information value. This indicates that there is no added value for using a more expensive ADC having 10 bits resolution.

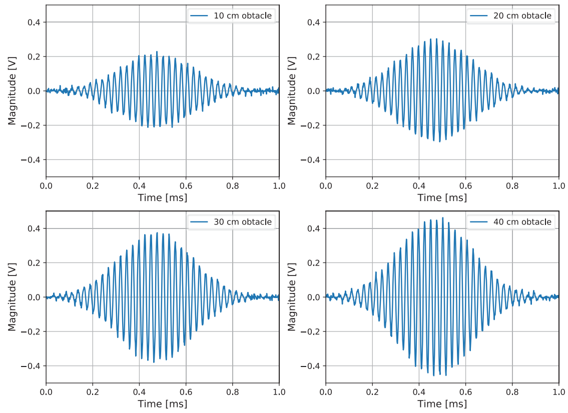

Fig. 3 Example of raw echoes (before pre-processing) from obstacles having different heights

The same height estimation performance could be achieved with an 8 bit ADC as with a 10 bit ADC. As the ADC resolution drops below 8 bits we see a drop in the value of the mutual information. This indicates that the height estimator performance will be degraded on a statistical level. By projecting these mutual information values on the derived Fano characteristic curves, it is possible to identify the expected error rate for the given number of classes in which the obstacle height is to be classified. This is of course assuming an optimal estimator or classifier is employed.

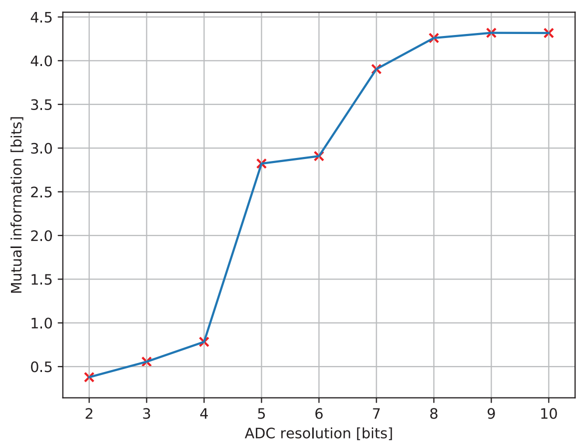

Fig. 4 Change in the mutual information value with change in the ADC resolution for the full dataset

Similarly, the mutual information is calculated for the dataset at different sampling rates and the results are presented in Fig. (5). It is directly observed that for sampling rate values above 250 kSample/s there is very little benefit to be gained in terms of mutual information. As sampling rate values drop beyond the 100 kSample/s mark, we see a very rapid drop in the mutual information value thus indicating rapid degradation in the ability to estimate the obstacle height by inspecting the ultrasonic signal output from the ultrasonic sensor. In a similar manner, by projecting the mutual information values on the derived Fano characteristic curves, it is possible to predict the performance of an optimal estimator in terms of statistical error rate given the number of height classes in which the estimator will classify the obstacle heights.

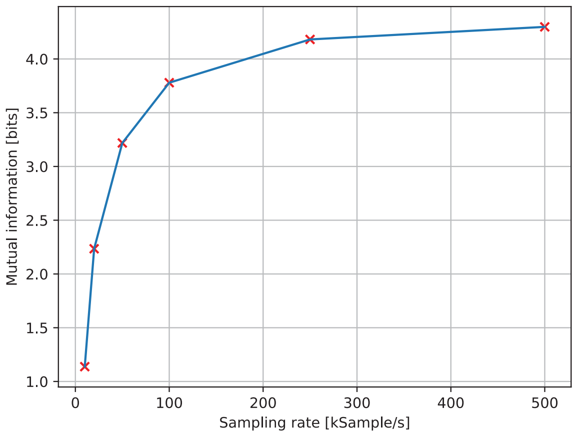

Fig. 5 Change in the mutual information value with change in the sampling frequency

V. Conclusion

The capability to estimate a feature of an obstacle by analyzing its echo signal that is detected by an ultrasonic sensor is quantifiable in terms of mutual information. This value may be used to determine if the estimation problem is unsolvable and whether there is no relationship between the signal generated by the sensor on the one hand and the change in the obstacle feature value on the other. Additionally, we may validate that there is enough mutual information between the signal and the feature for the feature to be estimated, given an appropriate estimator. Under the assumption that we have an optimum estimator, it is also possible to mathematically identify the maximum possible performance on a statistical basis, in terms of probability of error, using the Fano's inequality and the characteristic curves that are derived in this work.

We also see that for the practical application presented, which is classifying the height of obstacles based on their generated ultrasonic signal, the optimum digitization values are clearly identified using this methodology. This shows that using more expensive and capable ADCs will not provide additional benefit for this specific application. It also demonstrates that having less capable ADCs has a direct impact on the system's ability to perform the task of height estimation.

The presented methodology provides the means to clearly identify the needed resources based on the intended application thus preventing the failure to achieve the intended target of the ADAS and at the same time preventing the use of unnecessarily expensive components that would bring no extra value to the intended functionality. Applying this methodology to the different types of sensors in automotive industry shows very high potential in optimizing the overall cost and ensuring the delivery of ADAS functionalities.

References

[1] Fano, Robert M., and David Hawkins. "Transmission of information: A statistical theory of communications." American Journal of Physics 29 (1961): 793-794.
[2] Fisher, John W., Michael Siracusa, and Kinh Tieu. "Estimation of signal information content for classification." 2009 IEEE 13th Digital Signal Processing Workshop and 5th IEEE Signal Processing Education Workshop. IEEE, 2009.
[3] Kraskov, Alexander, Harald Stögbauer, and Peter Grassberger. "Estimating mutual information." Physical review E 69, no. 6 (2004): 066138.
[4] Moon, Young-I, Balaji Rajagopalan, and Upmanu Lall. "Estimation of mutual information using kernel density estimators." Physical Review E 52, no. 3 (1995): 2318.
[5] Battiti, Roberto. "Using mutual information for selecting features in supervised neural net learning." IEEE Transactions on neural networks 5, no. 4 (1994): 537-550.
[6] Peng, Hanchuan, Fuhui Long, and Chris Ding. "Feature selection based on mutual information criteria of max-dependency, max-relevance, and min-redundancy." IEEE Transactions on pattern analysis and machine intelligence 27, no. 8 (2005): 1226-1238.
[7] Fleuret, François. "Fast binary feature selection with conditional mutual information." Journal of Machine learning research 5, no. Nov (2004): 1531-1555.
[8] Liu, Huawen, Jigui Sun, Lei Liu, and Huijie Zhang. "Feature selection with dynamic mutual information." Pattern Recognition 42, no. 7 (2009): 1330-1339.
[9] Vergara, Jorge R., and Pablo A. Estévez. "A review of feature selection methods based on mutual information." Neural computing and applications 24, no. 1 (2014): 175-186.
[10] Horng, Ming-Huwi. "Multi-class support vector machine for classification of the ultrasonic images of supraspinatus." Expert Systems with Applications 36, no. 4 (2009): 8124-8133.
[11] Pereira, Wagner Coelho A., André V. Alvarenga, Antonio Fernando C. Infantosi, Leonardo Macrini, and Carlos E. Pedreira. "A non-linear morphometric feature selection approach for breast tumor contour from ultrasonic images." Computers in Biology and Medicine 40, no. 11-12 (2010): 912-918.
[12] Shekhar, Raj, and Vladimir Zagrodsky. "Mutual information-based rigid and nonrigid registration of ultrasound volumes." IEEE transactions on medical imaging 21, no. 1 (2002): 9-22.
[13] Prelov, Vyacheslav V., and Edward C. van der Meulen. "Mutual information, variation, and Fano's inequality." Problems of Information Transmission 44, no. 3 (2008): 185-197.
[14] Yang, Sheng, and Jun Gu. "Feature selection based on mutual information and redundancy-synergy coefficient." Journal of Zhejiang University-Science A 5, no. 11 (2004): 1382-1391.
[15] Cooper, Matthew, and Michael Miller. "Information gain in object recognition via sensor fusion." In Proceedings of the International Conference on Multisource-Multisensor Information Fusion (Fusion'98), vol. 1, pp. 143-148. 1998.
[16] Poepperli, Maximilian, Raghavendra Gulagundi, Senthil Yogamani, and Stefan Milz. "Capsule neural network based height classification using low-cost automotive ultrasonic sensors." In 2019 IEEE Intelligent Vehicles Symposium (IV), pp. 661-666. IEEE, 2019.
[17] Mohamed, Mohamed-Elamir, Heinrich Gotzig, Raoul Zoellner, and Patrick Maeder. "A Machine Learning Approach for Detecting Ultrasonic Echoes in Noisy Environments." In 2019 IEEE 89th Vehicular Technology Conference (VTC2019-Spring), pp. 1-6. IEEE, 2019.
[18] Mohamed, Mohamed-Elamir, Heinrich Gotzig, Raoul Zoellner, and Patrick Maeder. "A Machine Learning Approach for Ultrasonic Noise Suppression With Minimal Distortion" In 2019 IEEE International Ultrasonic Symposium (IUS2019), IEEE, 2019.