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Minimum Signal-To-Noise Ratio For High Classification Radar Accuracy

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Abstract—Radar sensors in automotive cars are crucial for detecting and avoiding obstacles, improving safety, and enabling advanced driver-assistance systems. The signal-to-noise ratio (SNR) is a significant metric in radar systems for detecting the target at the output of the radar receiver and classifying the images in the algorithm classification. The purpose of this study is to determine the minimum SNR of images and signals to achieve high classification accuracy. A public dataset based on impulse radar and the LeNet-5 CNN architecture were used. The simulations demonstrated that images with an 10 dB of SNR can be classified with a high accuracy of 98%, and a 0 dB SNR at the output of the radar receiver was reported to be the minimum SNR required at the front-end output.

Index Terms—SNR, Convolutional neural network, Radar, Classification, Accuracy.

I. INTRODUCTION

Radar technology is widely used in various industries to detect and track objects. In the automotive industry, hand gesture radars are implemented to provide a new level of interaction between drivers and their vehicles. It allows drivers to control various functions without physical touch. This enhances driving safety by minimizing distractions and reducing the need for drivers to look away from the road. With hand gesture recognition, functions such as adjusting the volume, controlling AC, and operating windshield wipers can all be performed without buttons. This improves the driving experience by making the interactions with the vehicle more convenient and intuitive. The use of hand gesture radars in the automotive industry is likely to become more widespread in the future as the demand for advanced driver-assist systems has grown. In radar systems, the amplitude or the power of the transmitted waveform is crucial for enabling sensing within the maximum range. However, the waveform amplitude alone does not lead to accurate measurements and analysis since the signal can be degraded by many impairments, such as clutter, noise and phase noise. Another significant metric for reliable measurement and analysis is the signal-to-noise ratio (SNR), which describes the difference between the desired signal and the different impairments translated into noise.

The SNR is a crucial metric for radar designers in designing the front-end of a radar system. It determines the system's ability to detect targets and reject interference. Designers usually design the radar front-end so that they can reach the highest SNR at the output of the radar [1–3]. On the other side, artificial intelligence (AI) researchers propose classification

algorithms and test their performances (accuracy, confusion matrix, precision, etc.) on an existed radar [4–6]. No link was established between the requirements of the classification algorithm and the radar system in terms of the SNR. The purpose of this study is to:

- determine the minimum SNR of an image ($\text{SNR}_{\text{image}}$) required to assure a high classification accuracy.
- use the minimum $\text{SNR}_{\text{image}}$ to estimate the minimum SNR required at the output of the radar front-end .

In this study, a public dataset and a fixed classification algorithm are used. Estimating the minimum SNR will help the designer to evaluate the system specification, and alleviate the system/design constraints. The remainder of this paper is organized as follows. In Section II, the signal-to-noise ratio is defined for each step of the radar pipeline. Section III introduces the architecture of the classification algorithm and the dataset. Section IV presents the simulation results. Finally, the conclusions and discussion are presented in Section V.

II. SIGNAL-TO-NOISE RATIO DEFINITIONS

Radars use electromagnetic waves to detect objects. The transmitter sends an RF signal, which is then reflected back by the target. The reflected signal is detected by the radar's receiver and then processed for target detection and classification, as illustrated in Fig. 1. Extracting features from the receiver output signal is challenging because it requires a clear signal with a good SNR value. The signal-to-noise ratio is a basic tool used to measure the system performance and sensing capabilities for a radar. As the name indicates, SNR is the ratio of the signal power to the noise power, where both powers are measured within the same bandwidth and can be expressed as follows:

$$\text{SNR} = \frac{P_{\text{signal}}}{P_{\text{noise}}} \quad (1)$$

Where:

$$P_{\text{signal}} = 1/M \sum_{i=1}^M S_i^2 \quad (2)$$

where S is a discrete signal and M is the signal size.

An alternative definition of SNR is given in [7], assuming that the signal and noise are random variables:

$$\text{SNR} = \frac{\mathbb{E}[S^2]}{\text{Var}[S]} = \frac{\sum_{j=1}^M S_j^2}{\sum_{j=1}^M [S_j - \sum_{j=1}^M S_j/M]^2} \quad (3)$$

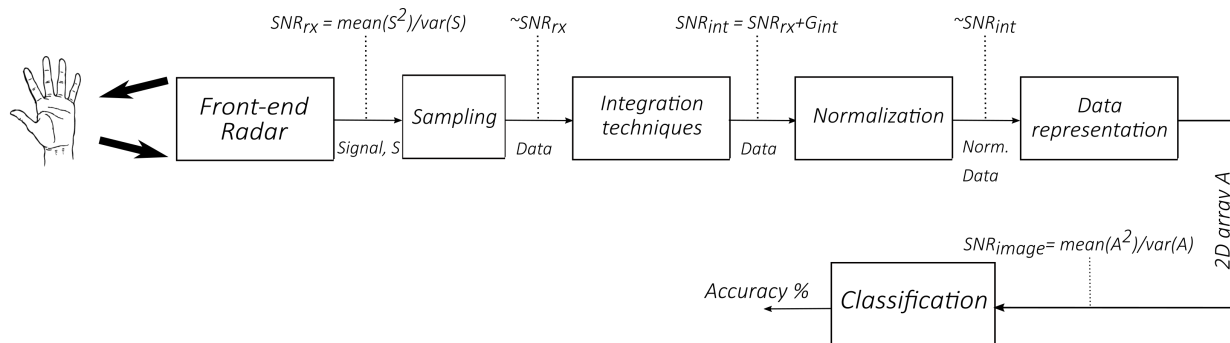


Fig. 1: Definition of the SNR at different location of the radar pipeline

where $\mathbb{E}[S]$ and $\text{Var}[S]$ denote the mean and the variance of the signal, respectively.

The SNR of the receiver output SNR_{rx} can be defined using the equation 3. This analog signal is converted in the sampling step to the digital domain using an analog-to-digital converter (ADC) to process it in the upcoming stages. An ADC is usually selected to meet signal requirements, such as bandwidth, resolution, linearity and SNR. This quantization step introduces quantization noise, which is neglected in this study. Consequently, the SNR at the output of the sampling step is approximately equal to SNR_{rx} .

At this stage, the SNR is sometimes not sufficiently high to detect targets and to avoid false detections. Integration techniques can be applied using multiple transmit pulses to improve SNR. The integration allows to improve the SNR by an integration gain G_{int} that differs depending on the type of integration, coherent or noncoherent. The SNR can be then expressed as follows:

$$SNR_{int} = SNR_{rx} + G_{int} \quad (4)$$

After integration, normalization can be implemented to adjust the digital signal based on the highest level and the SNR remains constant. The data are then concatenated in a 2D-array of fast and slow time [8], where the fast time represents the distance of the hand from the radar, and the slow time represents the frames transmitted by the radar. To classify a hand gesture, the array can be represented in several formats: time-range, time-Doppler, range-Doppler, time-time, etc. These images (2D-array) are gesture signatures performed in front of the radar and are used as inputs to feed the classification algorithm. Many metrics have been tested to quantify and measure image quality in digital image processing, such as Mean Square Error (MSE), signal-to-noise ratio (SNR), and Peak Signal-to-noise ratio (PSNR). MSE and PSNR are basically used to measure the quality between the original image and the processed image [9]. However, SNR describes the quality of the image by comparing the level of the signal contained in the image with the level of noise. Mathematically, SNR image is defined as the ratio of the mean

to the variance of the signal intensity [9, 10]:

$$SNR_{image} = \frac{\mathbb{E}[A^2]}{\text{Var}[A]} \quad (5)$$

Assuming that the digital image size is $N \times M$, equation 5 can be written as:

$$SNR_{image} = \frac{\sum_{i=1}^N \sum_{j=1}^M A_{i,j}^2}{\sum_{i=1}^N \sum_{j=1}^M [A_{i,j} - \sum_{j=1}^M A_{i,j}/M]^2} \quad (6)$$

The SNR of each signal at the output of the radar is crucial in determining the input image quality of the classification algorithm and thus the total accuracy. Moreover, if the image quality is poor, the decision made by the classification algorithm may be incorrect and the gesture can be misclassified. An image is a concatenation of multiple signals that are important and nonimportant. Important signals are the signals of the target reflection and are responsible for the image quality, whereas the non-important signals are the signals of the background. The average SNR of the signals presented in an image of signal concatenation (fast-slow time map) is:

$$SNR_{average} = \sum_{i=1}^N \frac{\sum_{j=1}^M A_{i,j}^2}{\sum_{j=1}^M [A_{i,j} - \sum_{j=1}^M A_{i,j}/M]^2} / N \quad (7)$$

The SNR of an image and the average SNR of the signals in the image are two different measures that represent different aspects of the image quality. The overall SNR of the image considers the entire image and the average SNR of the signals in the image considers the individual signals in the image. However, these two values are not directly comparable. In the context of hand gesture recognition using a CNN as a classification algorithm, the average SNR of the signals is not as important as the SNR of the signals that contain information about the gesture because the goal is to accurately recognize the gestures. The high maximum SNR of the signals in the image can be considered the SNR of the important signals and is used as the first estimation of the minimum SNR at the output of the front-end system.

III. CONVOLUTIONAL NEURAL NETWORK AND DATASET

A. Convolutional neural network architecture

CNN is a subtype of artificial neural network (ANN) that employs the mathematical operation **convolution** and

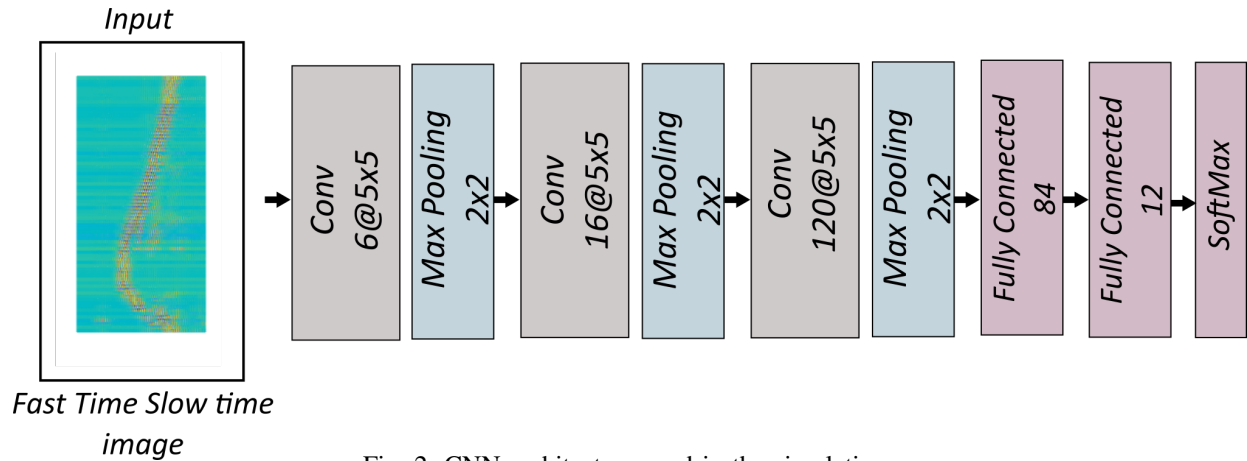


Fig. 2: CNN architecture used in the simulations

is primarily designed for image recognition and processing applications [11]. It is pointed out as one of the most efficient and suitable solution for image classification for many advantages. CNN is primarily a feature extractor. It automatically detects the prominent features without human supervision. The exploitation of this advantage is mainly revealed by the use of large and complex datasets, such as CIFAR-10, 100 and ImageNet. In addition to that, the CNN reduces the dimensionality of images without losing information, which helps to reduce storage space and remove redundant features. CNN are extensively used in human hand gesture classification, with high accuracy reported in [13–16]. Indeed CNN can classify up to six gestures from five people with an accuracy of 91% in [13], whereas the support vector machine (SVM) reported a lower accuracy of 83.3%. Moreover, in [15] 14 hand gestures were classified using a deep convolutional neural network (DCNN) and an accuracy exceeding 95% was shown with very low confusion between gestures. Better performances were also reported in [16] for image classification in comparison with belief propagation (BP), and SVM. The performance of a CNN depends mainly on the quality of the signal information present in the input data, its complexity, and hyperparameters (HP) such as the epochs, size of the input data, and size of the kernels. The SNR of the images at the input of the CNN played a crucial role in improving classification performance [9]. Consequently, this study focuses on the impact of the SNR on the accuracy of the CNN architecture using the following steps:

- use a fixed CNN network architecture, fixed dataset and hyperparameters.
- generate datasets with different levels of SNR from a public dataset.
- train and evaluate the network.

The model used for this study was similar to that of the LeNet-5 architecture. The main motivation to experiment with LeNet-5 is its good performance for image classification. The proposed CNN-based model is shown in Fig.2 consisting of three sets of convolution layers followed by an average pooling layers and two fully connected layer. Finally, a softmax

classifier is used to classify the images into their respective classes. The activation of these convolutional layers is tanh activation function. To train this architecture, we randomly selected 650 images per SNR as training data. In total 650 x 12 images are used for training model. The learning rate started at 0.003, the number of epochs was set to 10, and we saved the trained model to evaluate the other datasets with different SNRs. The CNN architecture was implemented in MATLAB R2021a.

B. Dataset

The number of public datasets of hand gesture recognition with radars is increasing to allow testing algorithm performance, such as the DopNet, DeepSoli, MCD-Gesture, and IR-UWB datasets reported in [18]. The IR-UWB dataset was the first public radar dataset of 12 dynamic hand gestures acquired using an impulse radio ultra-wideband (IR-UWB) radar, the 8.745GHz XeThru X4 UWB radar from Novelda. The dataset contains a 2D fast time slow time matrix, 90 x 189 images, encompassing 12 gestures across 8 users, each of which made 100 sessions of gestures, totaling 9600 samples. Fig. 3.a shows an example of a fast-time slow-time image. The gestures were recorded for 4s in front of three radars: left radar R_L , right radar R_R and top radar R_T as the Fig. 3.b presents. The matrices were provided without pre-processing (raw data) and with pre-processing (clutter removed).

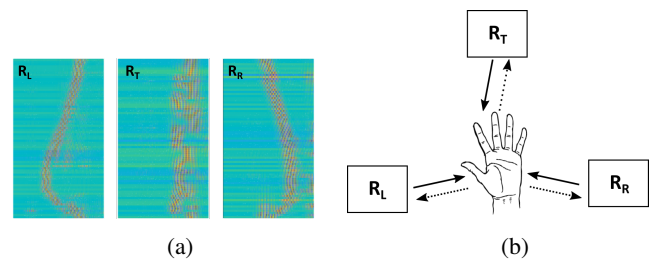


Fig. 3: (a) IR-UWB dataset: fast time slow time of the left radar R_L , top radar R_T and right radar R_R of the left-right swipe gesture [18]. (b) Position of the radars in the dataset.

IV. SIMULATION RESULTS

As discussed earlier, the quality of the signal presented in the images plays a dominant role in the image quality and, thus, in the accuracy of image classification. In this section, we attempt to estimate the minimum SNR required at the radar output to ensure high accuracy ($\geq 98\%$) of the classification algorithm for hand gesture applications. Fig. 4 presents the classification accuracy of each datasets of the three radars as well as the average accuracy with different SNRs range from -4dB to 20dB . The average accuracy was obtained by averaging the classification accuracies of the three radar systems. As shown in Fig. 4. In the high SNR region ($\text{SNR} \geq 10\text{ dB}$), the task of identifying the images is relatively easy for all three radars, and the accuracy is higher than 98% . The classification accuracy greatly decreases with a decrease in the SNR, making classification difficult and with errors. The classification accuracy of the radar top is superior to that of the other two radars, which is normal because the top radar can capture all hand gesture features and movements compared to the other radars. We can conclude that images with an SNR higher than 10 dB can be accurately classified and important features can be accurately extracted. In [16, 17], images with 10 dB of SNR were accurately classified with high accuracy using algorithms based on CNN. The dataset of 10 dB $\text{SNR}_{\text{image}}$ can be used to estimate the SNR of the important signals and thus the minimum SNR at the output of the radar SNR_{rx} allowing for good classification accuracy. The results showed an average SNR in the range $0\text{dB} \leq \text{SNR}_{\text{image}} \leq 1\text{dB}$ for the three radars. This range of SNR means that the signal and the noise of a signal are slightly at the same level.

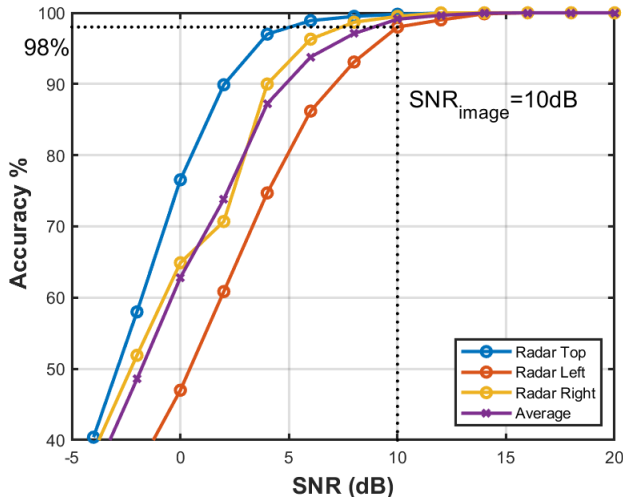


Fig. 4: Classification accuracy of three radar datasets and average accuracy versus $\text{SNR}_{\text{image}}$.

V. CONCLUSION

In this paper, we simulated the impact of $\text{SNR}_{\text{image}}$ on the accuracy using the LeNet-5 architecture and a public dataset. We simulated three different radar datasets (left, right, and top) of two-dimensional time-time images and used them to train

the designed CNN. To determine the minimum $\text{SNR}_{\text{image}}$ for a high classification accuracy, we evaluated its recognition accuracy under different $\text{SNR}_{\text{image}}$ levels. Our simulations demonstrated that all three radar datasets achieved a recognition accuracy of above 98% when the $\text{SNR}_{\text{image}}$ was above 10 dB . The minimum SNR_{rx} of the signals at the radar output should be greater than 0 dB . In this study, a public dataset based on impulse radar of hand gestures and LeNet-5 were used. Consequently, the results may not be generalizable to other datasets and radar types. However, for the same type of radar and algorithm architecture, the results should be used in the first step, and other parameters can be tuned to achieve better accuracy.

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