Artificial Neural Networks Applied to Denoising Radar Data

Convolutional Autoencoder for Denoising Range-Doppler Maps in FMCW Radars

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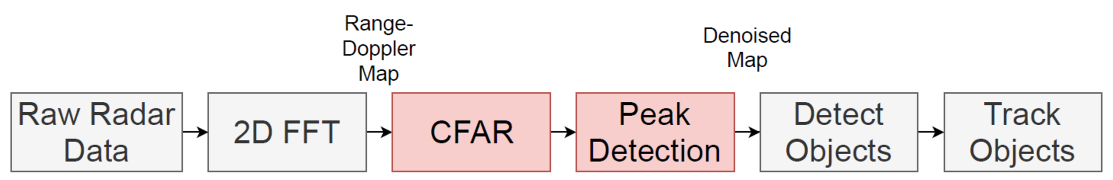
Introduction

The future road surveillance, as well for autonomous vehicles, is going towards multi-sensor systems capable of detecting, classifying and tracking objects such as pedestrians, cyclists and cars. However, cameras depend highly on good lighting, and laser sensors (such as LiDAR) are expensive and fragile. Radars, on the other hand, are cheap, robust and can work regardless of weather or light conditions.

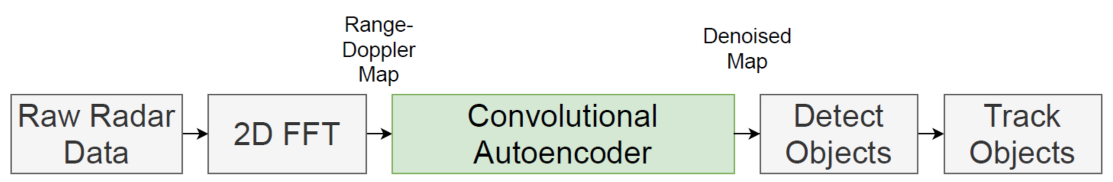
Frequency-Modulated Continuous-Wave (FMCW) radars can directly measure the distance to an object and their relative radial velocity. With this data, it is possible to build a Range-Doppler (RD) map. This map is a two-dimensional heat map, where one axis represents the distance between radar and object; the other represents the relative radial speed of them. A RD map can be treated as an image and, by doing so, it is possible to apply many known image processing techniques to it.

In this research, we propose a novel technique to reduce noise in Range-Doppler maps utilizing Convolutional Autoencoders (CAE) instead of a traditional Order Statistic Constant False Alarm Rate (OS-CFAR) method. As seen in Fig. 1, our goal is to modify the portion of the traditional denoising technique by applying a CAE. The advantages for doing this are various:

- CAE outperforms the traditional OS-CFAR method, especially in highly noisy situations.
- CAE learns patterns and can discern between noise and a moving object, therefore it is more robust.
- CAE can retrieve information bellow the noise level.



(a) Traditional object tracking scheme



(b) Proposed change

Figure 1: Simplified schematics of the traditional tracking and the proposed change.

CAE Architectures and Configurations

A Deep Convolutional Autoencoders (CAE) utilizes Convolutional Neural Networks (CNN) in a deep learning scheme to extract features from images or image-like objects. Like any other autoencoder, it has an encoder where the feature extraction occurs, and a decoder where the image is reconstructed. Unlike regular autoencoders, CAE can utilize deep learning for its benefit and, through a supervised learning process, can learn to identify objects and noise. Following Fig. 2, it is possible to see what occurs during the evaluation of an already-trained network. The encoder receives a noisy RD map featuring two people walking towards the radar to extract features and important shapes. The extracted features then pass through the decoder to reconstruct a noise-reduced map in the output, based on its training.

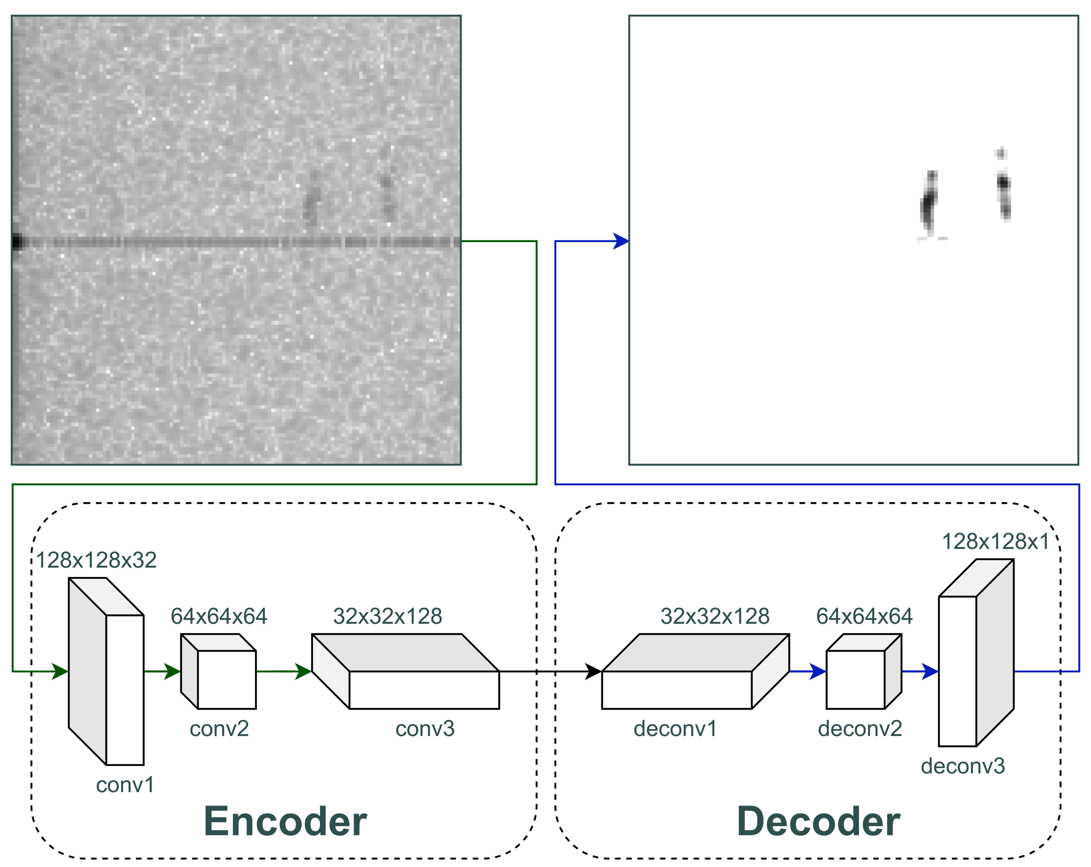


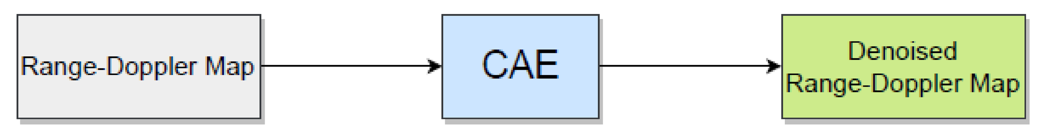
Figure 2: Noisy Range-Doppler map passing through a 3 layer encoder and 3 layer decoder to obtain a cleaner image.

An advantage of Artificial Neural Networks over the traditional methods is the ability to learn patterns. As seen in Fig. 3, a person walking on an RD map has certain patterns. Due to the difference in speed of legs and arms compared to the torso, a walking person appears to be a line-shaped object, compressing and stretching into a pattern that a human eye can identify and thus CAE can learn it.

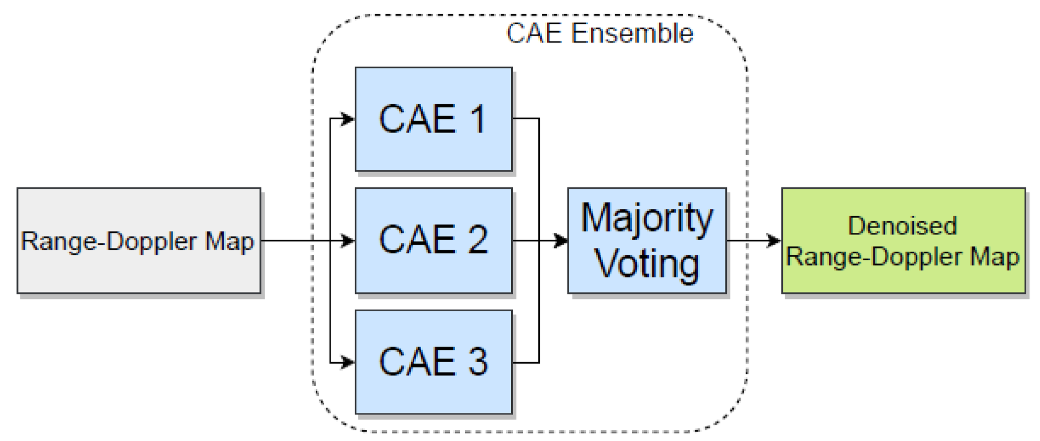
(a) (b) (c) (d) (e) (f)

Figure 3: Six frames of a person walking on an RD map, ordered by time - from frame (a) to (f).

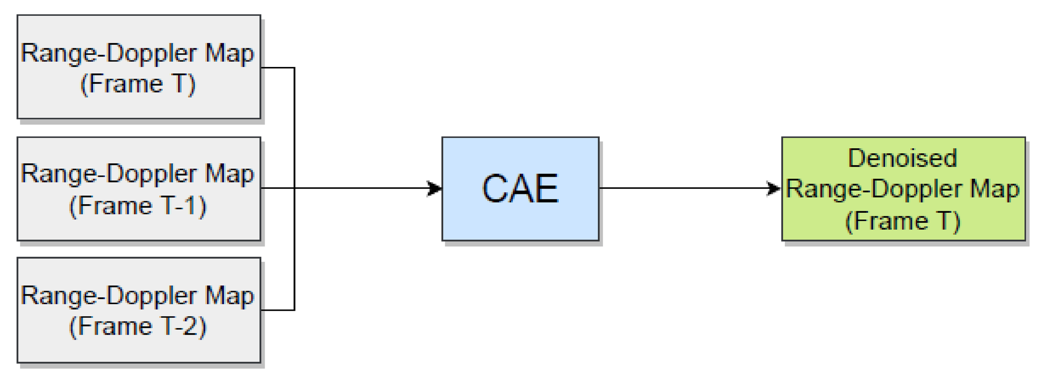
For this work we proposed and tested 4 systems based on the CAE architecture (Fig. 4): (i) a traditional 1 CAE that process one frame at a time; (ii) 3 CAE working in parallel, with different weights and biases, that process one frame at a time; (iii) 1 time-series CAE, that process the current frame and 2 previous frames; (iv) 3 time-series CAE working in parallel, processing three sequential frames.



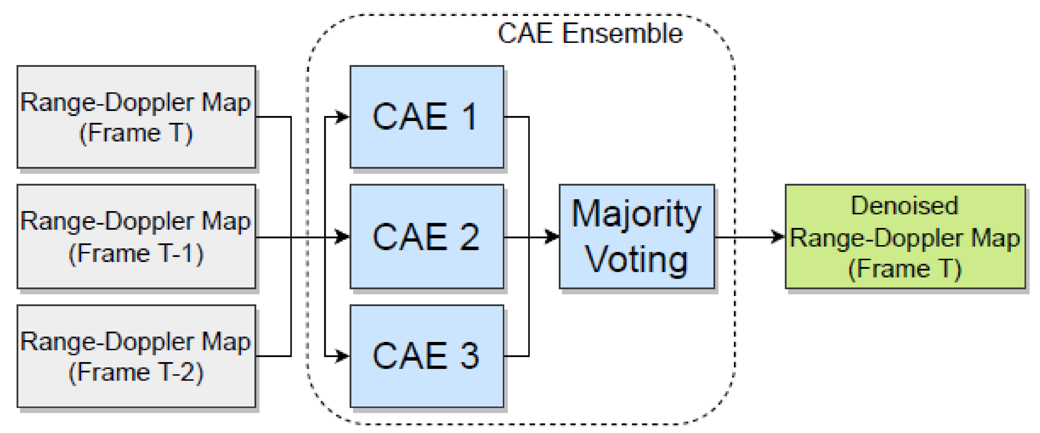
(a) 1 CAE - 1 frame



(b) 3 CAE - 1 frames



(c) 1 CAE - 3 frame



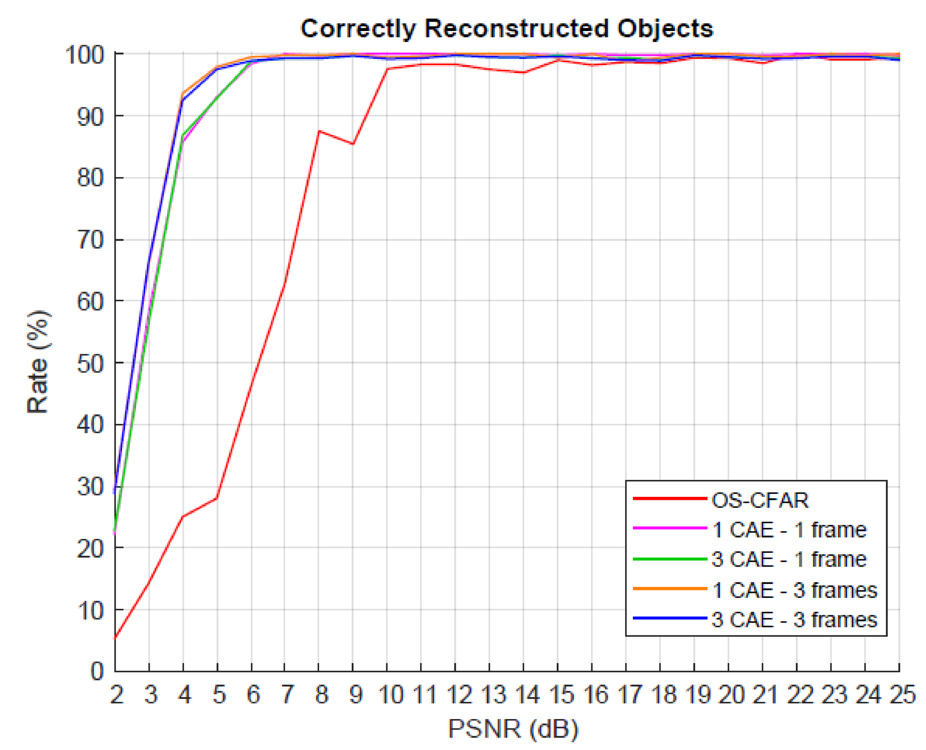
(d) 3 CAE - 3 frames

Figure 4: Different architectures using CAE.

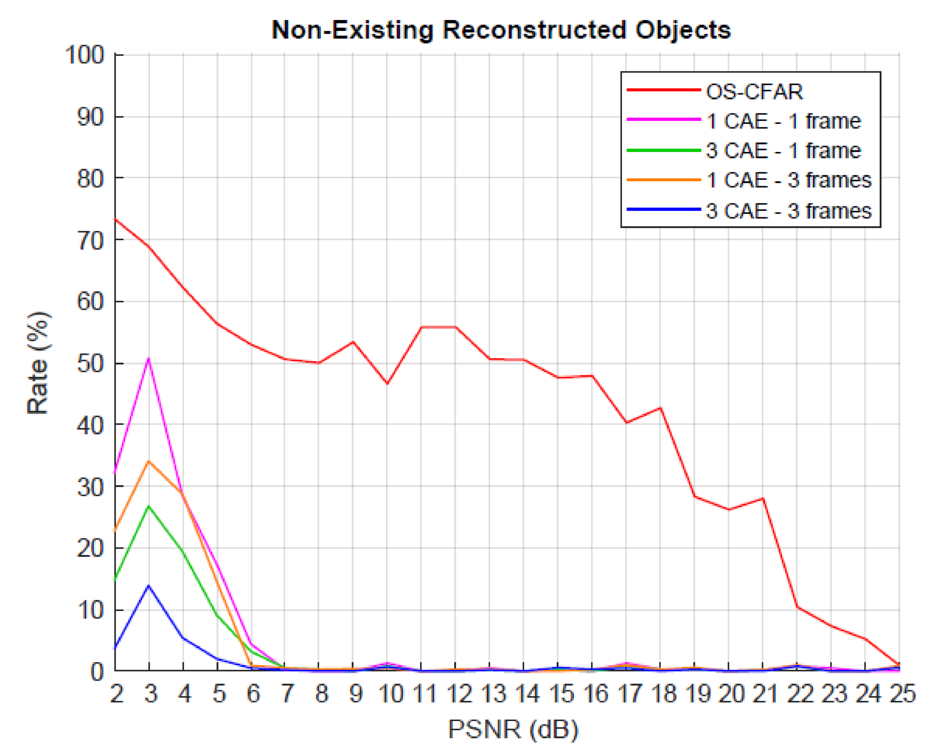
Experiments and Results

During this research, we have evaluated the four systems based on CAE over various noise levels. As the results are analyzed (shown in Fig. 5), it can be inferred that any CAE system at any noise level outperforms the traditional OS-CFAR.

We believe that the system using 3 parallel CAE and 3 sequential frames would be the most robust solution since it almost did not reconstruct non-existing objects (1.6% of frames) and it had the second-best correct reconstruction rate (94.6% of objects). If compared with OS-CFAR, this system is 17.5% more efficient at correctly reconstructing objects and 25 times better at not reconstructing non-existing objects.



(a) Percentage of objects reconstructed in the right place.



(b) Percentage of frames where non-existing objects were detected.

Figure 5: Result of five distinct systems performing with various noise levels - from a PSNR of 2 dB to a PSNR of 25 dB.

Conclusions

- Convolutional Autoencoders were tested in various architectures and configurations to reduce noise levels in Range-Doppler maps.
- In all architectures, CAE outperformed the traditional OS-CFAR method.
- The learning nature of CAE makes possible a better denoising.
- The passive nature of OS-CFAR shows limitations for objects bellow a certain threshold of noise.
- Improvement of 76.8% to correctly reconstruct objects and 188% for false positives.
- Important work with application in distant moving objects that are often below the noise level.