Proceedings of CONF-CIAP 2026 Symposium: International Conference on Atomic Magnetometer and Applications
DOI: 10.54254/2753-8818/2026.HZ27960

Radar Signal Processing Based on Complex-valued Convolutional Network

Mocheng Wu

Shenzhen College of International Education, Shenzhen, China
s23451.wu@stu.scie.com.cn

Abstract. Radar technology is deployed across a wide range of contemporary fields, and most of the radar signal processing tasks present the potential of being addressed using a complex-valued model. This paper presents a comprehensive review of the architecture of complex-valued convolutional neural network (CV-CNN) and discusses frameworks for its adoption in these application domains, regarding its superiority in preserving phase information and the beneficial inductive bias of the network compared to real-valued counterparts. Numerous methods used in different components of the CV-CNN architecture, involving complex convolution, complex activation function, and complex batch normalisation, are compared and discussed, and recommendations for implementation tailored to specific types of radar signal processing tasks are provided. The implementation of CV-CNN on radar signal processing missions greatly reduces the learning complexity and displays comparable performance with even higher training efficiency. This underscores a critical direction for future development: machine learning models should be designed to inherently respect the mathematical and physical laws governing the data, unlocking greater potential in signal processing and beyond.

Keywords: Complex-Valued Convolutional Neural Network, Radar Signal Processing, Complex-Valued Deep Learning, Interference Mitigation

1. Introduction

Radar is a type of electronic device that performs radio detection and ranging by transmitting electromagnetic waves and interpreting the received signal reflected after hitting objects, obtaining crucial information about the targets, such as distances and velocities. It has been widely used in multiple fields in society, such as weather monitoring, missile guidance, and sign detection, due to its capability of sensing information all-weatherly. Moreover, with the advancement and iteration of technology, the advent of new types of radar, such as synthetic aperture radar (SAR) and InSAR, occurs, enabling high-resolution SAR imaging with submeter-level or centimeter-level accuracy, regardless of weather conditions, like fog and cloud. As radar systems are increasingly used, there are some specific domains that require high precision and accuracy in target detection, such as autonomous driving. In these application fields, the accuracy of the results may be diminished due to several reasons, such as inevitable mutual interference caused by crowded radar sensors, resulting in degraded target detection, which may cause severe issues.

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In the past few decades, emerging technologies like deep learning (DL) have advanced rapidly, resulting in the advent of multiple types of neural networks, such as convolutional neural networks (CNN), fully connected neural networks (FCN), generative adversarial networks (GAN), etc. Among them, CNN has achieved great success in areas like natural language processing, image recognition, image classification, and so on.

Recently, numerous studies have found that using complex-valued convolutional neural networks (CV-CNNs) to process radar echo signals can have considerable effects on enhancing accuracy and also efficiency of radar signal processing compared to real-valued counterparts. The approach of using a complex-valued network is incentivised by the fact that radar signals are instinctively complex-valued. Hence, using CV-CNNs inherently offers distinct advantages, including increasing computational efficiency and preserving phase information, which is essential for processes like angle estimation and image interpretation. Fuchs proposed a model that implemented core CV-CNN operations, including complex convolution, complex batch normalisation (BN), and complex activation function [1]. Moreover, the inductive bias, which is directly built into the network architecture, makes the fundamental rules for complex numbers calculation embedded in the network, enabling the model's architecture to align with the underlying physics of the data. Thus, a large number of parameters that are used to discover and explore these rules are not needed, which enhances several kinds of efficiencies. Eventually, models using CV-CNNs achieved a better performance on IM with higher F1-Score and lower error vector magnitude (EVM) and peak phase mean squared error (PPMSE), using less data than models using real-valued convolutional neural network (RV-CNN) [1]. Wang's team's model follows a similar approach, yet uses a time-frequency representation (t-f representation) as input instead of a range-doppler map (RD-Map), which is especially advantageous when identifying non-stationary interference [1, 2]. Additionally, the network employs a prior-guided loss function, alleviating the reliance of the model on the dataset and boosting the generalisation ability. A hyperparameter is also used to avoid overfitting and to make the training process converge faster. Eventually, comparable performance is achieved on the CV-FCN model by using only 1/8 of the full data in low SINR scenarios compared to real-valued counterparts [2]. Gao's team also found that CVCNN can be used to enhance radar imaging, obtaining a higher imaging quality and efficiency [3]. Moreover, Zhang and Ren employed CVCNN on SAR image classification, discovering that the model is capable of acquiring a higher overall accuracy (OA) than using RVCNN [4, 5].

Despite these promising individual demonstrations, the existing literature remains fragmented, comprising case-specific solutions without a unified theoretical and practical framework to guide the application of CV-CNNs across the diverse landscape of radar signal processing tasks. Therefore, the objective of this paper is to provide a proper framework that guides the utilisation of CVCNN in radar sensing. The remainder of this article is organised as follows. Section II introduces the current application of CVCNN in different areas of radar signal processing. Section III presents the basis of radar signal processing, which assists in the elaboration of the importance of using complex-valued CNNs. A unified governance framework of CVCNN and its comparable virtues are presented in Section IV. Elaborations on several specific application fields are presented in Section V. Finally, conclusions are drawn in Section VI.

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2. Case description

2.1. General architecture and core advantages of CV-CNN

Complex-valued convolutional neural networks (CV-CNNs) have transitioned from a theoretical concept to a practical tool in radar signal processing, demonstrating superior performance across a diverse range of tasks by leveraging the innate complex nature of radar data. Up to now, the framework of CV-CNN used in the radar field consists of an input layer, complex convolution layers, complex activation functions, complex pooling layers, complex batch normalisation layers, and potentially complex fully connected layers, which are all extended to the complex domain [3]. Some models also introduce methods to further enhance computational efficiency and generalisation capability, like using a refined loss function or activation function, and so on.

In the recent decade, CV-CNN has been successfully applied in multiple domains of radar signal processing. The majority of the cases utilise the fact that complex numbers occur either naturally or by design in wave signals, providing a superior advantage of preserving core information such as phase, and also regarding that the inherent fundamental mathematical relationship between the real and imaginary parts of the signal can be maximised, enabling a substantial enhancement in data processing efficiency, instead of training extra amount of data to discover the rules embedded innature [3]. These theoretical advantages have been empirically validated in several key application domains within radar signal processing, as detailed below.

2.2. Application cases in radar signal processing

The applications of CV-CNNs in radar can be broadly categorized into three areas: (1) interference mitigation in radar signals, (2) classification of radar images, and (3) target detection and recognition. CV-CNN models have achieved promising results in tasks such as denoising RD-maps and mitigating interference in frequency modulated continuous wave (FMCW) or chirp sequence (CS) radar systems, commonly using RD-map or t-f spectrogram as input, complex convolution, and complex-valued rectified linear unit (CReLU) as activation function, extended to the complex domain [1, 2]. Supervised learning and loss function are employed by feeding real-life radar signal data and adding simulated interference. The introduction of the inductive bias to the network also causes it to align better with the physical characteristics of the radar signal, resulting in better performance in low signal-to-interference-plus-noise ratio (SINR) scenarios, while using a training dataset with reduced size and achieving better generalisation capability than real-valued counterparts [2].

In the field of image classification, CV-CNN is commonly used for polarimetric SAR (PolSAR) image processing, consisting of components like complex input-output layers, a pooling layer, a fully connected layer, and backpropagation [3]. Image pixels of the polarimetric SAR image can be classified into given terrains, like forest, grass, water, buildings, wheat, etc., achieving a higher OA and lower overall error than RV-CNN according to the experimental results [3]. A novel architecture of CVCNN, however, proposed three new approaches for PolSAR image classification, including amplitude-based max pooling, complex-valued nonlinear activation, and a cross-entropy loss function, showing discriminative capabilities in feature preserving, feature extraction, and classification accuracy [4]. This demonstrates that CV-CNNs are not merely an incremental improvement but a paradigm shift for PolSAR image analysis, enabling more accurate and physically consistent interpretation of scattering mechanisms [4].

DOI: 10.54254/2753-8818/2026.HZ27960

3. Basis of radar signals and complex-valued data

3.1. Basis of radar signal processing

Currently, common radar systems contain pulse doppler radar, synthetic aperture radar (SAR), phase-modulated continuous wave (PMCW) radar and so on, where pulse doppler radar utilises doppler effect between pulse trains to obtain velocity information of moving targets, SAR radar synthesizes a large aperture by processing a series of pulse echoes which are sent and received by radar platform in different locations while moving, obtaining results with high resolution without being affected by light conditions, though certain weather conditions (e.g., heavy rain) can attenuate signal.

Radar systems, particularly Frequency-Modulated Continuous Wave (FMCW), follow a specific signal processing chain to obtain range and velocity of the target. Firstly, the frequency synthesiser (Syth) sends a frequency-modulated signal via the transmitting antenna (Tx ant). Then the electromagnetic wave hits the target and is reflected and is received by the receiving antenna (Rx ant) as an echo signal, which is further sent to the mixer component along with a portion of the transmitted signal, producing their sum and difference frequency. The signal will then pass through the low-pass filter (LP filter), removing the high-frequency sum component, and the intermediate frequency (IF) signal will be acquired. For a stationary target, the frequency of this IF signal is proportional to the target's range. For a moving target, the frequency is a function of both range (via the chirp timing) and radial velocity (via the Doppler effect). Subsequently, the analogue IF signal will be sent to an analogue-to-digital converter (ADC) and converted into a digital signal for further processing. It is critical to note that from this stage onward, the signal is typically represented and processed as complex-valued In-Phase and Quadrature (I/Q) data. For each transmitted chirp, Fast Fourier Transform (FFT) is employed to transform the digital signal from the time domain to the frequency domain [6]. A range spectrum will be output after FFT, where the peaks indicate the targets. Afterwards, Doppler-FFTs are performed for each range bin, and the Range-Doppler Map (RDM) will be obtained as a result, with each peak in the 2D map representing a target and its location in the map corresponding to a specific range and velocity.

It is important to note that the electromagnetic wave itself is a real-valued physical signal. However, its mathematical representation and baseband signal after IQ demodulation are most efficiently described using complex exponentials. This leads to the next section, where the complex-valued essence of the wave signal will be elaborated.

3.2. The physical significance of complex-valued data

Firstly, the radio frequency signal (RF-signal) received by radar or the signal transmitted by the antenna is real-valued, represented by the expression $sr(t) = A(t)\cos(2\pi fct + \phi(t))$, where $A(t)$ represents the amplitude information of the signal, and $\phi(t)$ is the phase information. During the process of in-phase quadrature (IQ) demodulation, the signal is split into in-phase, the RF receiver down-converts the signal to baseband by mixing it with a local oscillator signal $\cos(2\pi fct)$, to generate in-phase (I) component, and with a quadrature local oscillator signal, $-\sin(2\pi fct)$, to generate the quadrature (Q) component [7]. After low-pass filtering, these become the baseband I(t) and Q(t) signals. They respectively construct the real and imaginary parts of the signal.

After carrying out algebra operations, a complex-valued signal $x(t) = I(t) + jQ(t) = A(t)e^{j\Phi(t)}$, containing both amplitude and phase information, is obtained. Amplitude reveals the energy intensity of the received signal, enabling target detection and preliminary discrimination.

DOI: 10.54254/2753-8818/2026.HZ27960

Meanwhile, the phase contains range, radial velocity, and angle information of the targets, which are crucial in processes like constant false alarm rate (CFAR) detection and angle estimation. Amplitude primarily reflects the radar cross-section (RCS) of the target and propagation loss.

3.3. The inductive bias advantage: embedding physical constraints into CV-CNNs

When using RV-CNN models, the phase information will either be neglected or the real and imaginary parts will be input along two separate real-valued channels, leading to real and imaginary parts being processed independently [1]. This independent processing violates the fundamental physical constraint that I and Q are orthogonal components of a single complex entity, governed by strict mathematical rules (e.g., $j^2 = -1$) [4].

Suppose a real-valued network is used to learn the relationship between the real and imaginary parts. In that case, RV-CNN is coerced to learn the pre-existing statistical correlation of real and imaginary parts from the beginning; it will need to be fed with many more parameters and a dataset, and consume much more time to approximate the ideal result [5]. Moreover, the relationship learnt is usually imperfect since the relation is found relying purely on data, which may lead to distorted phase information, which is not sufficient for tasks requiring high phase precision, affecting the result of any further processing.

Adopting a complex-valued convolutional neural network provides an inductive bias, decreasing the degree of freedom of the network and fundamentally causing data to obey the arithmetic rules of complex numbers. By designing every component of the network, such as convolution, batch normalisation, and activation function, to operate natively in a complex domain, the network's operation is restricted to the standard algebraic rules of complex-valued numbers, which reduces the complexity of the learning problem [1]. This significantly enhances learning efficiency and model performance by being guided by the inductive and hard-coded bias without wasting computations to discover the pre-existing physical features of complex numbers. This aligns perfectly and seamlessly with the complex-valued baseband representation of the radar signal's nature, allowing its phase information to be conserved and achieving the same performance using a training dataset with reduced size. In essence, CV-CNNs enforce physical consistency by construction, whereas RV-CNNs must learn it approximately from data—an inefficient and often imperfect process.

4. Complex-valued Convolutional Neural Network

4.1. History of CV-CNN

The fundamental theory and architecture of deep CV-CNN were first systematically proposed by Trabelsi et al. in their 2018 work 'Deep Complex Networks', standardizing the core components of CV-CNN, encompassing complex BN, complex weight initialization, and complex activation function, providing a foundation for training more complicated CV-CNN [8]. This occurred at a time when the technology of RV-CNN was already rather mature, and the advantage of extending it to a complex domain is discussed. Later on, CV-CNN is gradually applied to different fields, such as target detection and interference mitigation.

4.2. Architecture of CV-CNN

The architecture of CV-CNN introduced in this paper contains an input layer, convolutional and pooling layers, fully connected layers, and an output layer. After preprocessing the data, various types of data, according to the application field, are fed into the input layer, followed by the process

DOI: 10.54254/2753-8818/2026.HZ27960

of feature extraction. This is performed in the convolutional layer, which employs a complex-valued nonlinear activation function, such as CReLU and modReLU, and a pooling layer. Convolution is carried out between the input data and multiple convolutional kernels, usually 3 × 3 in size, where desired features are contained. After applying the activation function to the result, the feature maps with reduced spatial dimension are obtained. The pooling layer will then further extract the core feature of the data. After that, data is fed into the fully connected layer, where the final classification or regression task will be performed. The loss function and training methods such as backpropagation are utilised to optimise the whole model.

4.2.1. Complex convolution

By convolving the input complex-valued feature map (or vector) h = x + jy, with the convolution kernel W = A + jB, obtaining W * h = (A * x – B * y) + j(A * y + B * x), where A and B are real matrices and x and y are real vectors. Hence, (A * x – B * y) is the real part of the convolution, whereas (A * y + B * x) is the imaginary part. This could be seen as a real-valued convolution defined by real part weighting A and imaginary part weighting B mutually, enforcing the network to learn the interactive relationship between the real and imaginary parts.

4.2.2. Complex activation function

In the training process of CV-CNN, an activation function is required to implement a nonlinear transformation on complex numbers, and the function has to be differentiable at the same time, ensuring the requirement for backpropagation is fulfilled. The mainstream activation function used in CV-CNN is the ReLU function. The advantage of ReLU and its variants is that it is non-saturating for positive inputs; hence, it help mitigate the vanishing gradient problem that may be encountered when using saturating functions like sigmoid or tanh. Being not bound in at least one direction is particularly beneficial in addressing the issue of vanishing gradient in carrying out backpropagation when using a saturated activation function like the sigmoid function, and accelerating the training process [9]. The omission of negative values provides a certain level of sparsity, resulting in a lower degree of information coupling. Additionally, the simplicity in calculating its derivative allows faster convergence of the network. Therefore, ReLU is the most prevalent activation function used in CNN training, and most of the CV-CNN architectures nowadays use variants of ReLU as an activation function.

According to Liouville's theorem, a function that is holomorphic everywhere on the complex plane and bounded must be constant. Boundedness is often desirable to promote training stability and avoid runaway activation values, which can cause gradient explosion, and differentiability is vital in ensuring that backpropagation can be done. This means that, in the complex-valued context, the choice of activation function involves a sacrifice of either boundness or differentiability. The most common path is retaining boundness instead of restricting perfect differentiability. The representations of this type of complex activation functions are CReLU and modReLU. CReLU is defined as:

$$CReLU(z) = ReLU(\Re(z)) + jReLU(\Im(z)) \tag{1}$$

In here, the real and imaginary parts of the data are being independently carried out by ReLU. The merits of ReLU are reserved, yet it deals with real and imaginary parts separately and fails to

DOI: 10.54254/2753-8818/2026.HZ27960

take advantage of the mathematical property of complex numbers completely. On the contrary, the modReLU function perfectly solves this issue, as it preserves the phase. It is defined as:

$$\text{modReLU}(z) = \text{ReLU}(|z| + b)e^{i\theta_z} = \begin{cases} (|z| + b)\frac{z}{|z|} & if \ |z| + b \geq 0, \\ 0 & otherwise, \end{cases} \tag{2}$$

where b is a learnable parameter. The function employs ReLU on |z| + b, and the result is multiplied by the unit vector $\frac{z}{|z|}$ of the complex number z. Hence, only the modulus of the complex number is altered; the phase is entirely kept the same, which is significantly helpful in applications that require critical phase information. The other path is designing functions that are holomorphic in some domain, while sacrificing boundedness, such as using zReLU. zReLU is defined as follows:

$$z\text{ReLU}(z) = \begin{cases} z & if \ \theta_z \in \left[0, \frac{\pi}{2}\right], \\ 0 & otherwise, \end{cases} \tag{3}$$

The complex number will be activated only when it is in the first quadrant; otherwise, the result will be zero. Although the function is indeed holomorphic in some regions, its boundlessness can be detrimental to network training since it can make the training process more susceptible to instability and gradient explosion.

4.2.3. Complex batch normalisation

During the process of network training, batch normalization is needed to ensure that the data samples have a similar distribution, hence speeding up the learning process and convergence of the neural network. As for CV-CNN, a common initial approach is to apply standard BN to the real and imaginary parts separately. This method has rather low computational cost and is easy to implement. This approach ignores the correlation between the real and imaginary parts. A more principled method is to use a complex BN, which whitens the data using a 2D covariance matrix [8].

4.2.4. Complex pooling

CNN models require a pooling layer to extract the most significant and effective features. An amplitude-based method can be adopted for complex-valued max pooling. The complex-valued feature map will be separated into real and imaginary ones, and the amplitude of every position on the feature map can be calculated [4]. In each pooling window, the maximum amplitude and output will be found. This allows the reduction of the dimension of the feature map and provides translation invariance.

5. Application of CV-CNNs on radar signal processing

Modern radar systems often operate in a complicated electromagnetic environment. In the context of autonomous driving, undesired radar signals with similar or the same frequency may enter the receiver, forming interference. This raises the probability of mutual interference, causing severe issues such as ghost targets, false alarms, and missed detections [10]. Higher accuracy of target detection is also crucial in ensuring the safety of autonomous driving. Additionally, CV-CNN could be a robust tool in radar image interpretation, especially for terrain classification.

DOI: 10.54254/2753-8818/2026.HZ27960

In order to address those problems, the following part will introduce a lightweight CV-CNN framework for the three main application fields: interference mitigation, SAR image classification, and target detection. The network architectures for the feature extraction process are mainly the same. First of all, raw complex data needs to be fed into the input layer. For IM, the inputs could be interfered with RD-maps. For image classification, the complex patch of PolSAR image could be the input, and for target detection, complex SAR images are the inputs. A complex convolutional block could include complex convolution, an activation function, and BN. The complex convolution layer will strictly follow the formula $W * h = (A * x – B * y) + j(A * y + B * x)$ mentioned in the previous section to ensure that the network only learns and carries out operations in the complex domain. For interference mitigation, if the primary goal is to recover the magnitude of the signal, CReLU could be adopted as an activation function due to its computational simplicity. However, it is crucial to note that this choice destroys the phase information. If the task requires reconstruction of a clean complex signal, such as for subsequent angle estimation or coherent processing, a phase-preserving activation function like modReLU is mandatory, despite its higher computational cost. Then, a complex BN should be applied. The complex convolutional block is followed by the pooling layer, where amplitude-based max pooling can be implemented [4]. The part containing a complex convolutional block and a pooling layer can repeat for a finite number of times. The depth of the network and the number of kernels per layer are hyperparameters. Grid search is needed to optimize the configuration in order to achieve a balance between performance and efficiency.

After feature extraction, the architecture shows variances in different applications. For interference mitigation, a fully convolutional network (FCN) architecture is typically used. One or more complex-valued convolutional layers are usually employed. No fully-connected layer is required, since the input and output are both sequences, and the spatial dimension needs to be preserved. As the task emphasises local filtering and reconstruction, the network can be relatively shallow. In SAR image classification, a fully connected layer is normally employed after flattening the feature map into a one-dimensional vector. As for target detection, the structure is rather complicated. Generally, a region proposal network (RPN) may be required to predict candidate anchor boxes and an objectness score for the targets. After that, fully-connected or convolutional layers will classify each candidate box, and in the end, bounding boxes will be output.

6. Conclusion

This paper analyzes the significance of using complex-valued CNNs rather than real-valued counterparts. The intrinsic complex-valued nature of the radar signal integrates seamlessly with the extension of the network to the complex domain, allowing decreased problem complexity and higher learning efficiency to be achieved. The basics of radar signal processing and CV-CNN architecture are discussed, showing how IQ demodulation results in a baseband signal that has low frequency and contains both amplitude and phase information. Different components of the CV-CNN model are elaborated, involving benefits and shortcomings of some alternatives, e.g., implementing conventional BN on real and imaginary parts separately, and using CReLU discards the correlation between I/Q and destroys phase information, respectively, despite their operational simplicity. A couple of frameworks for the main application of CV-CNN in the radar signal processing domain are suggested. These frameworks maximise the advantage of CV-CNN in preserving phase information and present core value in training efficiency, which displays enormous potential and preponderance in the signal processing field. This research, however, is subject to several limitations. The study on efficiency and performance improvements of using CV-CNN largely relies on secondary data and lacks the use of primary data. The utilisation of CV-CNN on

DOI: 10.54254/2753-8818/2026.HZ27960

radar signal processing is still a newly developed and emerging field, and limited cases on each application domain can be found. Future studies may set up an actual model and training to assist research.

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