

Complex-Valued CNN and Its Application in Polarimetric SAR Image Classification

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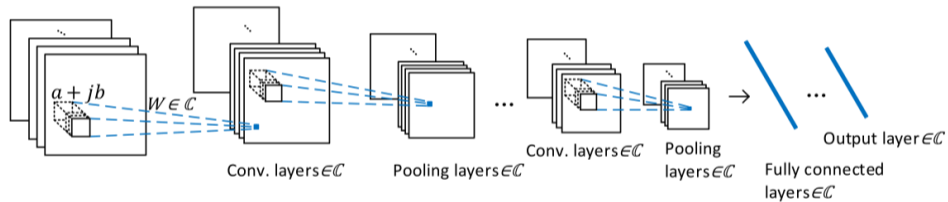
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Introduction

- ▶ The Authors of the paper is purposed a CNN which fully based on complex values.
- ▶ We have quite good performing RV-CNN then why Authors purposed this network?
- ▶ There is some data set which well represented in complex values rather than real values like SAR images.
- ▶ If we have to implement RV-CNN on this kind of data then we have to ignore some part of data.
- ▶ In my presentation I will focus on describing CV-CNN and results of the paper.

Preprocessing & Training



Architecture of CV-CNN

- ▶ The architecture of a CV-CNN can be regarded as a variant of the deep neural networks.
- ▶ 1) Convolution -> In the convolutional layer, the complex output feature maps $O_i^{(l+1)} \in \mathbb{C}^{W2 \times H2 \times I}$ are computed by the convolution between all the previous layer's input feature maps $O_i^{(l)} \in \mathbb{C}^{W1 \times H1 \times I}$, and a bank of filters $w_i^{(l+1)} \in \mathbb{C}^{F \times F \times K \times I}$ and then bias $b_i^{(l+1)} \in \mathbb{C}^I$, where \mathbb{C} denotes the complex domain and the superscript is its dimension. Where $W2 = (W1 - F + 2P)/S + 1$ and $H2 = (H1 - F + 2P)/S + 1$

$$\begin{aligned}
 O_i^{(l+1)} &= f(\Re(V_i^{(l+1)})) + jf(\Im(V_i^{(l+1)})) \\
 &= \frac{1}{1 + e^{-\Re(V_i^{(l+1)})}} + j \frac{1}{1 + e^{-\Im(V_i^{(l+1)})}} \quad (1)
 \end{aligned}$$

$$\begin{aligned}
 V_i^{(l+1)} &= \sum_{k=1}^K w_{ik}^{(l+1)} * O_k^{(l)} + b_i^{(l+1)} \\
 &= \sum_{k=1}^K (\Re(w_{ik}^{(l+1)}) \cdot \Re(O_k^{(l)}) - \Im(w_{ik}^{(l+1)}) \cdot \Im(O_k^{(l)})) \\
 &\quad + j \sum_{k=1}^K (\Re(w_{ik}^{(l+1)}) \cdot \Im(O_k^{(l)}) \\
 &\quad + \Im(w_{ik}^{(l+1)}) \cdot \Re(O_k^{(l)})) + b_i^{(l+1)} \quad (2)
 \end{aligned}$$

Architecture of CV-CNN

- ▶ 2) Pooling -> A straightforward extension of average pooling from real to complex can be defined as,

$$O_i^{(l+1)}(x, y) = ave_{u,v=0,\dots,g-1} O_i^l(x.s + u, y.s + v)$$

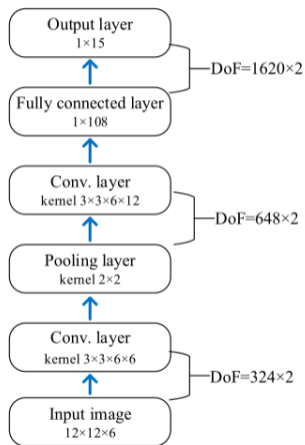
, where g denotes pooling size and s is the stride.

- ▶ 3) Complex Backpropagation -> The error can be described as a loss function E , for exempling using the classic least- squared error in CV-CNN. By computing the error gradient with respect to parameters $(\partial E/\partial w)$, the updating rule is $w \leftarrow w - \eta (\partial E/\partial w)$, where η is the learning rate.

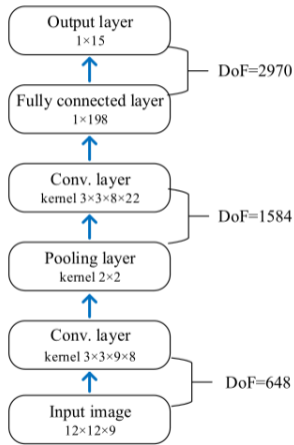
Error Function

$$E = \frac{1}{2} \frac{1}{N} \sum_{n=1}^N \sum_{k=1}^K [(\Re(T_k[n]) - \Re(O_k[n]))^2 + (\Im(T_k[n]) - \Im(O_k[n]))^2].$$

CV-CNN and RV-CNN



(a)



(b)

Flevoland SAR Dataset



(a)



(b)

- | | | | | |
|-------------|------------|-------------|-----------|-------------|
| ■ Stembeans | ■ Peas | ■ Forest | ■ Lucerne | ■ Wheat |
| ■ Beet | ■ Potatoes | ■ Bare soil | ■ Grass | ■ Rapeseed |
| ■ Barley | ■ Wheat 2 | ■ Wheat 3 | ■ Water | ■ Buildings |

(c)

Result Comparison

Class	CV-CNN	RV-CNN
Stem beans	98.8	97.5
Peas	98.7	97.4
Forest	96.8	96.0
Lucerne	98.1	94.5
Wheat	95.0	93.5
Beet	97.6	97.8
Potatoes	96.7	95.6
Bare soil	98.8	99.9
Grass	90.0	94.3
Rapeseed	92.0	92.1
Barley	94.5	86.2
Wheat2	94.2	97.2
Wheat3	96.6	95.6
Water	99.4	98.5
Buildings	83.2	80.0
Overall Accuracy	96.2	95.3
Overall Error	3.8	4.7
OA with Postprocessing	97.7	97.2

Conclusion and My Opinion

- ▶ Paper is well explained but no code and dataset link provided.
- ▶ It's showing good result in POLAR SAR image classification tasks. Exploration need to use CV-CNN in other image classification tasks

Thanks for attention!!
Questions???