Classification of Remotely Sensed Images using Deep Learning and Multiresolution Analysis

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Outline

Classification

A large number of semantic classification methods utilizing wavelet features have been developed

Deep learning for semantic classification

However, usage of ridgelet and contourlet is limited in context of deep learning

Need of Multiresolution analysis

Difficult to analyze information content just from the pixel value

The local changes of the intensity of an image are more important than the gray level intensity of that image

Different resolution levels are suitable for different sizes of objects (Buildings, shopping malls, small houses)

Wavelet based MRA

A sample image (only for illustration)

One level wavelet decomposition

Two level wavelet decomposition

Contourlet transform

Do and Vetterli (2002) grouped the wavelet coefficients to get a sparse image expansion

Double Filter Bank

Laplacian Pyramid

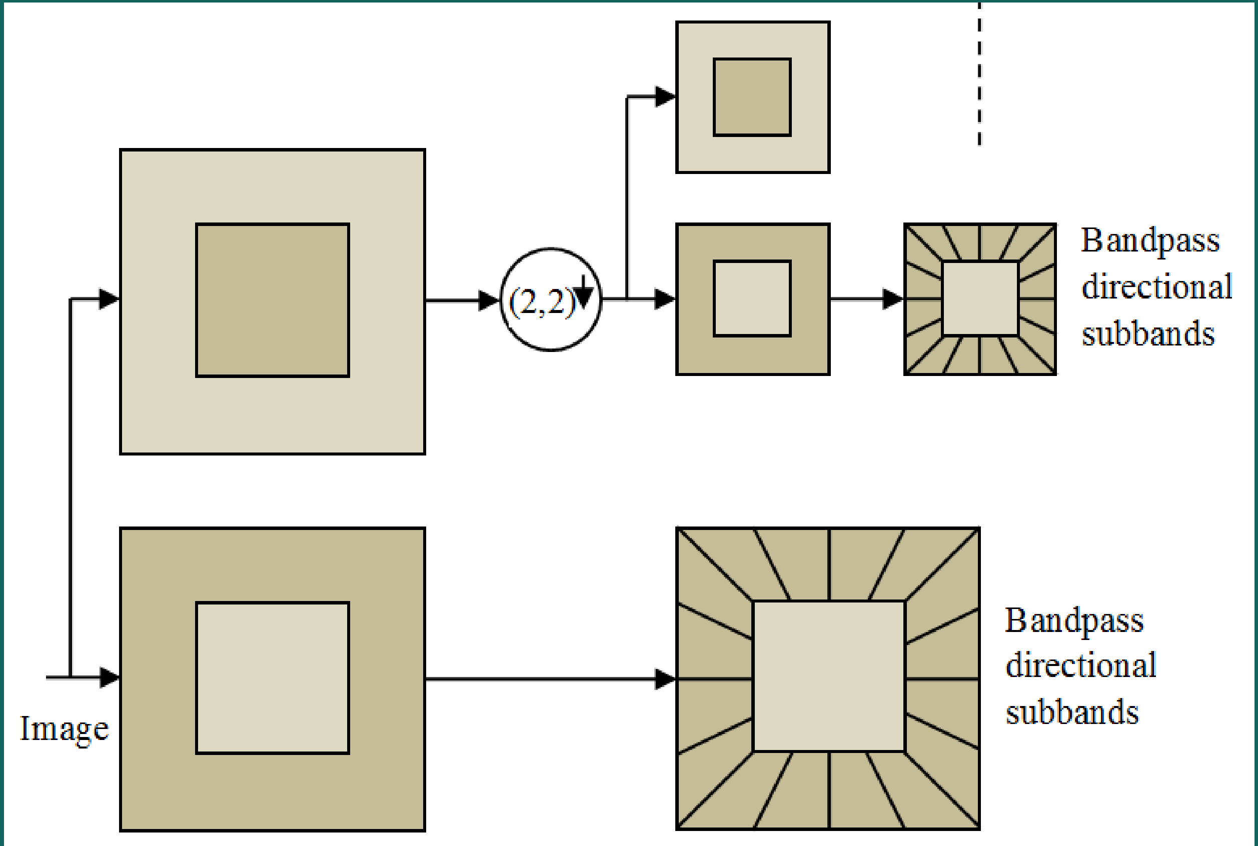
Directional Filter Bank

Expansion is composed of basis images oriented at varying directions in multiple scales, with flexible aspect ratios.

It can effectively capture the smooth contours with only a small number of coefficients

Implementation

(adapted from Do and Vetterli 2002)



Key Steps

By wavelet, ridgelet and conourlet decompositions, the features obtained at multiple scales, a concatenation with the corresponding stage from the contracting part is designed in the U-net.

Contracting part is used to extract the features of subbands

Every stage in the expansive part includes the up-sampling of the feature map, a concatenation block and a convolution block, which consists of a 3 × 3 convolution layer, a normalization layer and a rectified linear unit.

Kuwait city image (IRS)

Classified image using traditional U-net

Classified image using proposed MRA based U-net

Performance comparison

Model	Pixel Accuracy	IoU				
		Shallow Water	Build Up	Open Area	Road	Deep Water
Plain U-net	**82.86**	**79.92**	**77.62**	**56.60**	**46.81**	**88.86**
U-net+Wavelet	**89.22**	**98.44**	**83.08**	**69.66**	**56.85**	**98.69**
U-net+Ridgelet	**91.31**	**98.22**	**86.75**	**71.20**	**65.36**	**99.07**
U-net+Contourlet	**94.7**	**98.78**	**90.23**	**88.29**	**78.21**	**99.09**

Conclusion

Textural information from different subbands of MRA is extracted at various scales and integrated with U-net layers

MRA scales help extract different features of the objects to classify an image

The proposed method exhibits high classification accuracy with better edge continuity

Key References

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Thank You !

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