Joint use of Bivariate Empirical Mode Decomposition and Convolutional Neural Networks for Automatic Modulation Recognition

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Outline

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Goal and Context

AMR $\rightarrow$ Automatic Modulation Recognition

$\rightarrow$ act of determining the employed modulation type of an RF signal at given time, frequency and space

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How AMR has been achieved here:
→ Fusion of signal decomposition and Convolutional Neural Networks (CNN)

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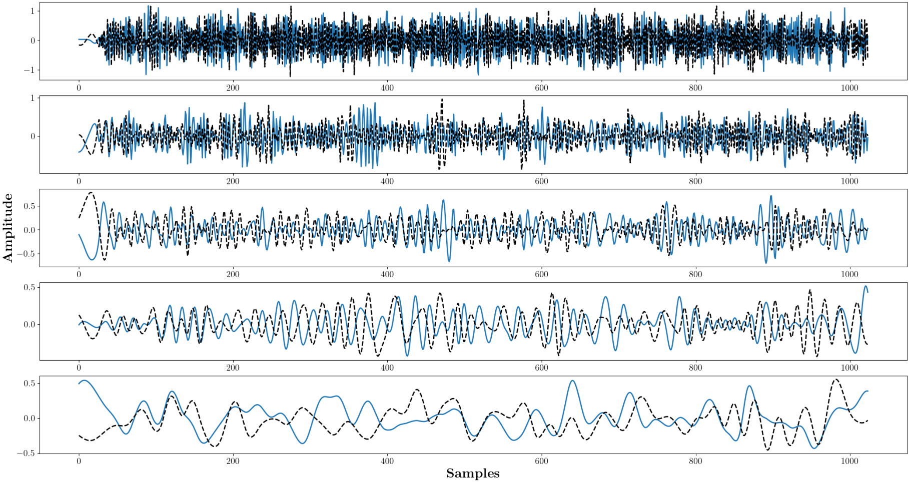
In digital telecoms: 2 variables $\rightarrow$ complex signal (IQ)
$\rightarrow$ justifies the use of Bivariate EMD (BEMD): [2]

Example: QAM16 decomposition



Outline

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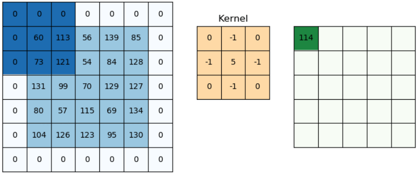

Figure: Kernel convolution [3]

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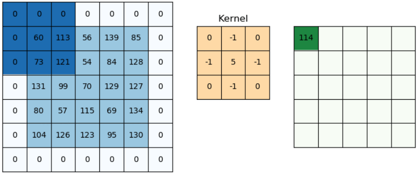

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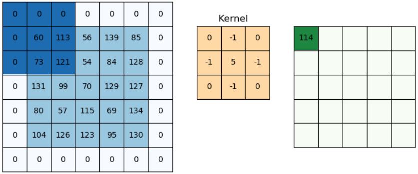

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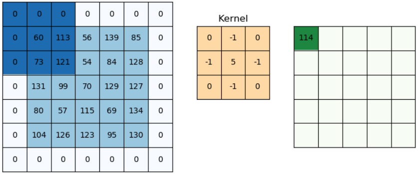

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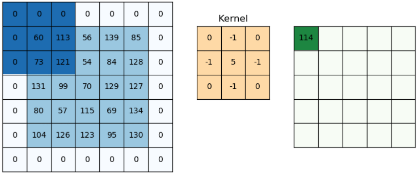

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- mainly used for image classification (mono and RGB)
- contains dense layer $\rightarrow$ permits multi class decision

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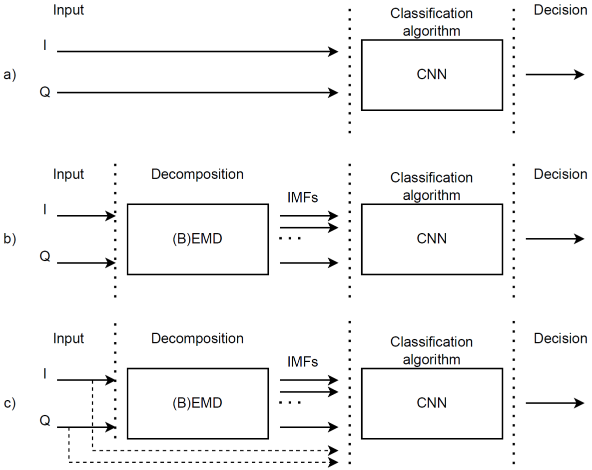
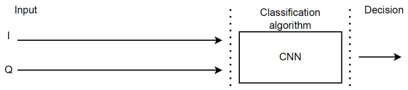
Process flows



Reference CNN architecture, IQ signal as input [4]



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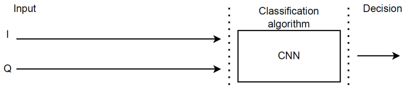

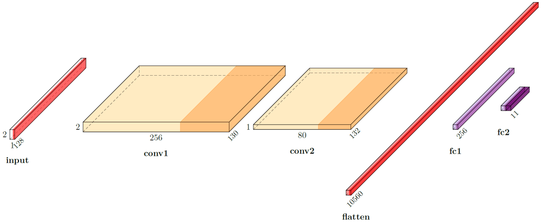

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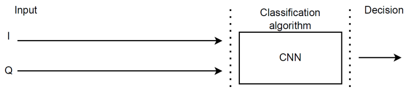
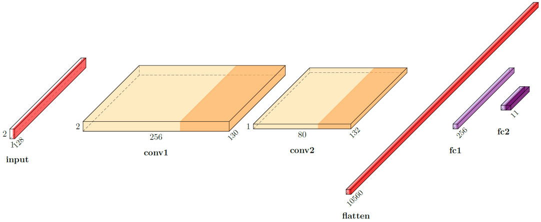
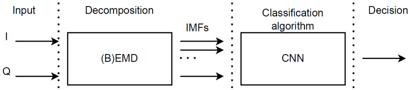




→ O'Shea's RadioML2016a dataset ([4]) is used

2D mode: place the IMFs one below each other



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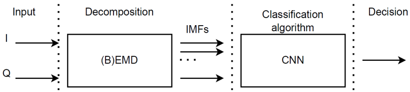

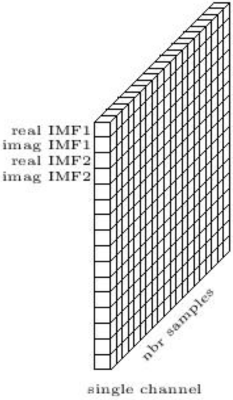

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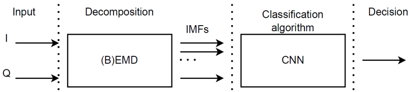

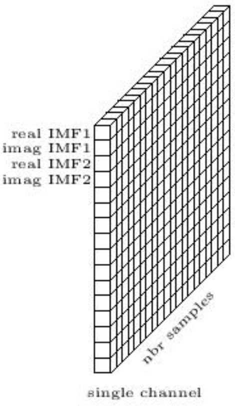

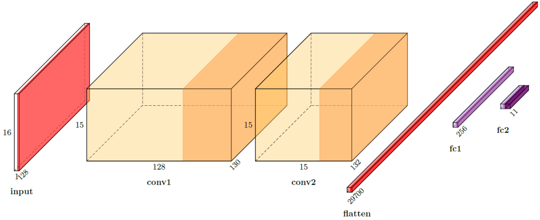

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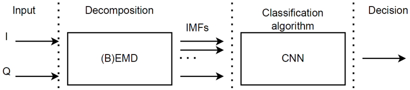

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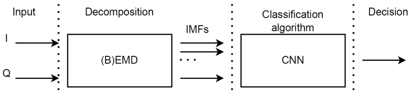

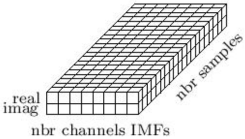

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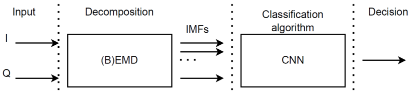

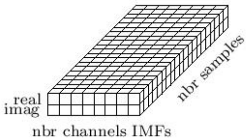

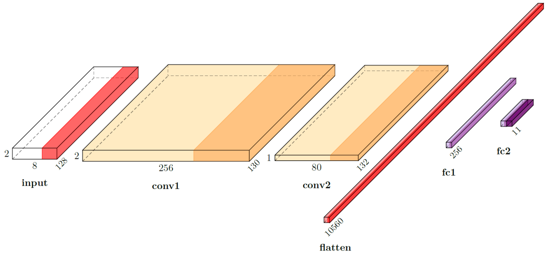

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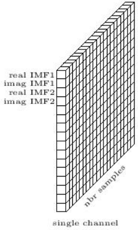
Overall accuracy improvement for each mode and w./w.o. original signal

	EMD	EMD +	BEMD	BEMD +
3D mode	0.7%	1.3%	2%	0.88%
2D mode	-12%	-4.1%	-10.3%	-3.8%



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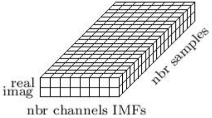
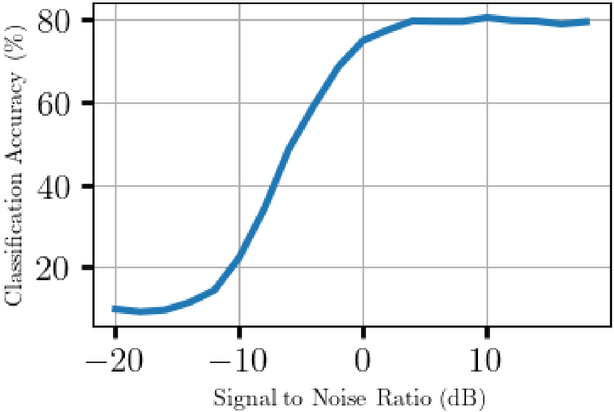
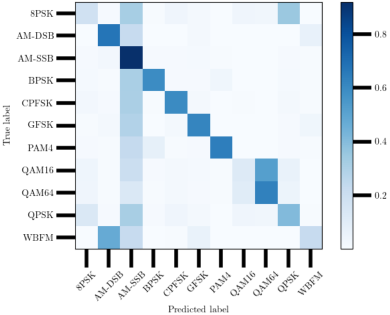


3D mode

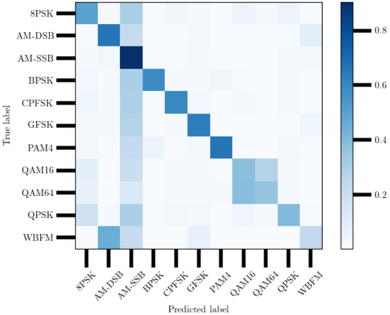
Classification accuracy (%) depending on SNR



Confusion matrices

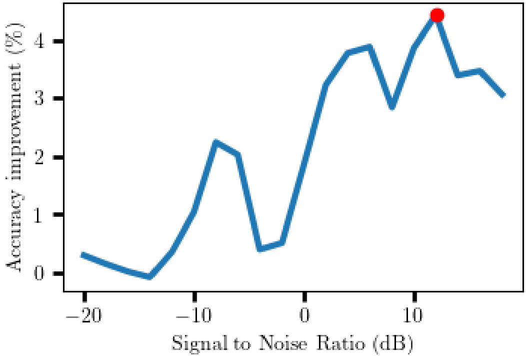


original result using IQ signal



new method using IMFs

Accuracy improvement (%) for all modulations depending on SNR



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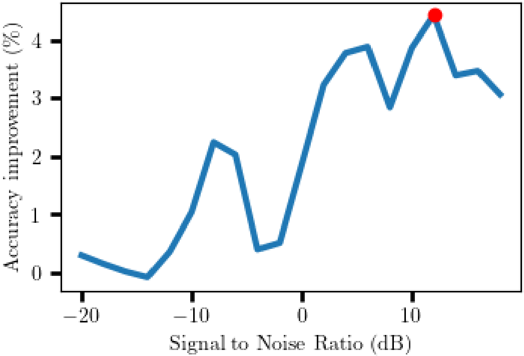

- 2 % overall accuracy improvement

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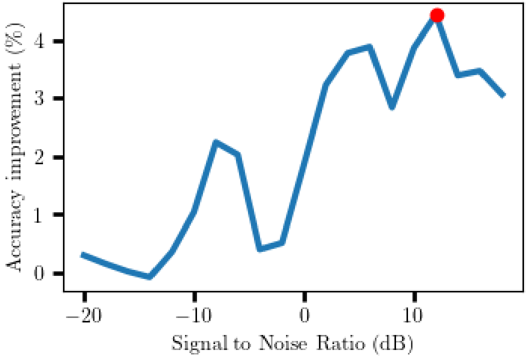

- 2 % overall accuracy improvement
- up to 4.4 % improvement

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- the paper also contains a discussion about complexity and decomposition times
- none of the CNN architectures have been optimized specifically for the use of the decomposed data

References [x] I

[1] N. Huang, Z. Shen, S. Long, M. Wu, H. Shih, Q. Zheng, N.-C. Yen, C.-C. Tung, and H. Liu, "The empirical mode decomposition and the hilbert spectrum for nonlinear and non-stationary time series analysis," *Proceedings of the Royal Society of London. Series A: Mathematical, Physical and Engineering Sciences*, vol. 454, pp. 903–995, 03 1998.

[2] G. Rilling, P. Flandrin, P. Goncalves, and J. M. Lilly, "Bivariate empirical mode decomposition," *IEEE Signal Processing Letters*, vol. 14, no. 12, pp. 936–939, 2007.

[3] `https://stackoverflow.com/questions/52067833/how-to-plot-an-animated-matrix-in-matplotlib`.

[4] T. J. O'Shea and J. Hoydis, "An introduction to deep learning for the physical layer," 2017.

Thank you

for your attention

Any question ?