The influence of Bivariate Empirical Mode Decomposition parameters on AI-based Automatic Modulation Recognition accuracy

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***Abstract*—On the one hand, the AMR (Automatic Modulation Recognition) realm has recently shown an increase of interest, particularly as an application for monitoring the physical layer of wireless transmissions. It consists in determining the employed modulation type of a sensed Radio Frequency (RF) signal at a given time, space and frequency. Moreover, it is a key component of intelligent radio systems such as Cognitive Radios (CR) that are key devices for Massive IoT (MIoT), autonomous cars, drones, 5G, 6G, etc. On the other hand, Bivariate Empirical Mode Decomposition (BEMD) is a signal decomposition method that can distill signals into a finite number of Intrinsic Mode Functions (IMFs) through a process known as sifting. BEMD is specifically designed to decompose bivariate (e.g. complex) signals, such as complex IQ samples of telecommunication data time series. The IMFs in conjunction with an AI architecture permits modulation classification.**

This paper specifically focuses on the influence of BEMD parameters on component extraction, namely the number of applied sifts and projections. The impact of linear interpolation method vs cubic spline interpolation method is also presented.

***Index Terms*—automatic modulation recognition, AMR, automatic modulation classification, AMC, cognitive radio, bivariate empirical mode decomposition, parameters BEMD, decomposition, convolutional neural networks, CNN**

I. Introduction

A. Context

The classification of modulation schemes traditionally involves two main approaches: the decision theoretic approach and the feature-based approach. However, with the advent of deep learning architectures [1], the domain of automatic modulation classification (AMC) has experienced a renaissance.

In [2], it has been proven that decomposing the signal using BEMD prior to introducing it into a convolutional neural network (CNN) type of AI architecture helps to extract interesting features and increases classification accuracy. In this paper, the impact of the BEMD decomposition parameters are analysed, namely the number of siftings, the number of projections and the type of interpolation used.

B. Data set

In order to classify modulations, an IQ database is required. The adopted dataset in this work is O'Shea's [3] RadioML2016a dataset. This dataset is a publicly available dataset consisting of complex-valued IQ samples, each being 128 samples long, and covering a wide range of radio signal modulations. The RadioML2016a dataset has been widely used in research on automatic modulation classification and machine learning for signal processing which enables thus performance comparison [4] [5]. It provides a valuable resource for researchers and developers working on the development of new algorithms for the classification of radio signals. The database contains single carrier modulations such as GFSK (Gaussian Frequency Shift Keying), 64QAM (Quadrature Amplitude Modulation), WBFM (WideBand Frequency Modulation) or QPSK (Quadrature Phase Shift Keying). There are a total 11 modulation schemes in the dataset and the signal to noise ratio in the dataset ranges from from -20dB to 18dB by steps of 2 dB, thus offering 20 different SNR values. This leads to a total of 220000 waveforms containing 128 samples each. Half of the dataset has been used for training, the other half for evaluation. It has to be noted that the dataset is not perfect [6] but that despite its flaws, it continues to be heavily used.

II. Decomposition method

A. BEMD (Rilling [7])

Bivariate empirical mode decomposition (BEMD) is a widely used method that extends the univariate EMD method to bivariate data, which is common in many contemporary data sets, including complex data. With the aim of extracting finer information to recover the modulation, such as amplitude and angular frequency, researchers have focused on developing approaches for decomposing bivariate or even multivariate data. In the context of telecommunications and software-defined radio, the main data series of interest are complex IQ samples, which makes BEMD a suitable approach.

The decomposition mechanism [8], also called sifting, consists in decomposing the input signal $s(t)$ into a finite number N of IMFs (Intrinsic Mode Functions) such that the signal can be expressed as:

$$s(t) = \sum_{i=1}^{N} \mathrm{IMF}_i(t) + r(t)$$

where $r(t)$ is the residue which may or may not have a linear trend.
Two important facts need to be highlighted in the BEMD method. Firstly, as presented in Fig. 1 displaying the decomposition steps, the mean is recurrently subtracted from the signal. Each of these subtractions are called sifts or siftings. The number of siftings can either be defined using a stopping criterion which is time expensive or simply predefined. Secondly, the method works by extracting rotating components using the mean of the envelope, which is like an enclosing tube around the signal. To create the lines that materialize the envelope, the signal is projected onto different directions or planes, resulting in a 2D signal on which the standard EMD methodology is applied. Four projections, for instance, could include extreme points in the top, bottom, left, and right directions. The rotating components can then be used to extract finer information, such as amplitude and angular frequency.

Algorithm 1 is the pseudocode representing one sifting process in the BEMD method.

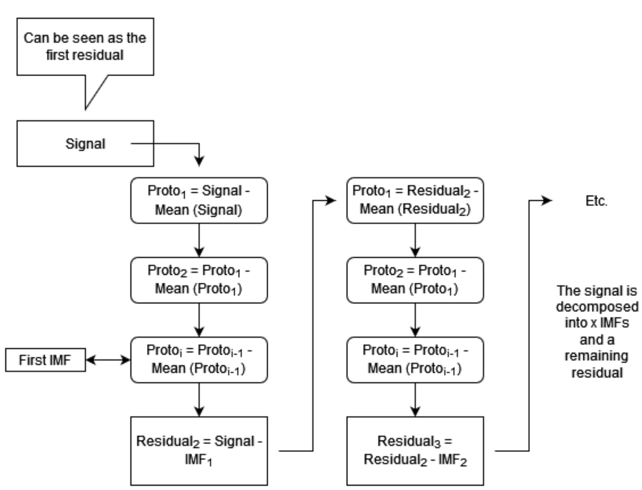

Fig. 1: Decomposition flow graph

Algorithm 1 The used BEMD algorithm from [7]

for $1 \leq k \leq N$ **do**
  `Project the complex valued signal` $x(t)$ `on direction` φ_k `(Plane P)`
  $\rightarrow p_{\varphi_k}(t) = \mathrm{Re}(e^{-i\varphi_k} x(t))$
  `Extract the locations` $[t_j^k]$ `of the maxima of` $p_{\varphi_k}(t)$
  `Interpolate the set` $(t_j^k, x(t_j^k))$ `to obtain the envelope curve in direction` $\varphi_k : e_{\varphi_k}(t)$
end for
`Compute the mean of all envelope curves` $m(t) = \frac{1}{N} \sum_k e_{\varphi_k}(t)$
`Subtract the mean`

B. Linear interpolation

In order to improve the overall computational speed, specifically regarding the envelope calculation, modifications have been made to the interpolation method. The interpolation step was found to be the most computationally intensive part of Algorithm 1 based on the results obtained from CPU profilers. Therefore, the cubic spline interpolation, which was previously used, has been replaced by a linear interpolation technique. Linear interpolation is a simple yet effective method for interpolation.

Fig. 2 shows how the signal's projections are used to recreate the envelope. The signal is depicted in blue and is a complex sinusoid $s(t) = sin(t) + jcos(t)$ The red line represents the mean of the envelope, it is calculated using the average of the projections. The other colors display the maxima and minima points of the signal that has been projected onto four planes at the angles 0, 45, 90 and 135 degrees.

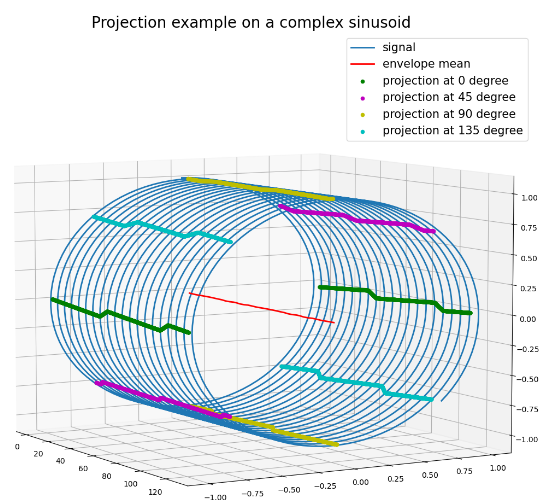

Fig. 2: Projection example for a complex sinusoid of amplitude 1V

Fig. 3, displays the real part of the first four intrinsic mode functions (IMFs) extracted from a Quadrature Phase-Shift

Keying (QPSK) modulation. These IMFs have been obtained through the BEMD method, utilizing four projections and three sifts. The difference between the plotted curves lies in the applied interpolation. Specifically, the blue curves were generated using cubic spline interpolation, whereas the orange curves were produced using linear interpolation. One can see that when using the cubic splines method, the number of remaining oscillations decreases faster with increasing IMF order.

III. Methodology

A. Artificial Intelligence architecture

Automated modulation classification (AMC) is the task of identifying the modulation type of a received signal at the receiver, which is typically a complex and challenging multi-class classification problem. To tackle this problem, deep-learning models are often employed. But designing such models involves consideration of various architectural parameters.

In this work, Convolutional Neural Networks (CNNs) were utilized for AMC. CNNs are a type of feed-forward neural network that has shown great success in processing and analyzing image and signal data. The main components of CNNs are its convolutional layers, which are responsible for convolving feature maps from previous layers with trainable kernels or filters. Additionally, the architecture includes fully connected or dense layers, which are Multilayer Perceptrons (MLPs) connected to the previous layer.

To improve the performance of the model, various techniques were used in this work, including ReLU activation maps (Rectified Linear Unit), padding and dropout layers. A flatten layer is used between the CNN and the dense layers. However, no pooling was employed, as the height of the data is small, and pooling could result in information loss due to averaging.

The corresponding convolutional layers (named conv1 and conv2) for this model have filter sizes of 1x3 for conv1 and 2x3 for conv2. The final dense layer has a size of 11, corresponding to the number of possible modulations, and includes a softmax activation layer for classification. The used CNN configuration is depicted in Fig. 5. The CNN architecture image have been created using PlotNeuralNet [9]. In Fig. 4 the best working input shape extracted from [2] is showed. The input shape has a height of two, containing the real (I) and the imaginary (Q) parts. The length is the number of samples (128) and the channels or depth is created with the extracted IMFs.

B. Information flow

The methodology's overall structure is illustrated in Fig. 6. The incoming Complex IQ data received by the receiver is subjected to a decomposition process using the Bidimensional Empirical Mode Decomposition (BEMD) method, with various parameters as mentioned in the beginning of the text. The extracted IMFs are then introduced to the CNN architecture which is trained to classify the used modulation type.

IV. Results

A. Parameters

The investigated parameters are the number of siftings for IMF extraction, the number of projections as well as the type of applied interpolation. The main characteristics are the overall accuracy taking into account all modulations and for all signal to noise ratios. The needed decomposition time is also added. Table I shows the time needed for the decomposition and is given for 100000 time series of length 128 and in minutes unit. It has been extracted from the mean of two measurements.

Table I also shows the accuracy results extracted from the mean of three full trainings. The accuracy results need to be compared to the overall accuracy using the signals IQ values along, thus involving no decomposition. In this original case, the accuracy is of 51.8 %. The calculations have been performed on an Intel SkyLake 2.60 GHz CPU on a high performance computing (HPC) cluster.

TABLE I: Overall accuracy depending on decomposition parameters

interpolation	siftings	projections	accuracy %	approx time (min)
cubic	3	4	53,86	84
		16	54,05	310
		64	53,67	1012
	10	4	53,96	269
		16	53,94	907
		64	53,76	3917
linear	3	4	51,92	39
		16	52,93	138
		64	53,71	676
	10	4	50,73	134
		16	50,61	530
		64	50,86	2302

B. Discussion

The assumption made to begin this work was that increasing the number of siftings and projections would give more refined intrinsic mode functions, increasing therefore the quality of the AI architectures input, and thus the classification accuracy.

This work shows that this is not the case and that these parameters have very little effects on the overall accuracy of the classifier.

This might be an unfavorable result in the sense that we can not improve the results considerably by refining the decomposition. However, it also means that it is not necessary to use high numbers of projections and siftings that increase the decomposition times drastically in order to get good results.

Regarding the complexity of the BEMD decomposition, it has been analysed in [10], [11] and [2]. Those references indicate that complexity can be simplified into into

$$P\ S\ n \log_2 n = \mathcal{O}(n \log n)$$

in which P represents the number of projections, S the number of siftings and n the length of the data.

Table I confirms this trend as the decomposition times are proportional to the number of applied projections and siftings.

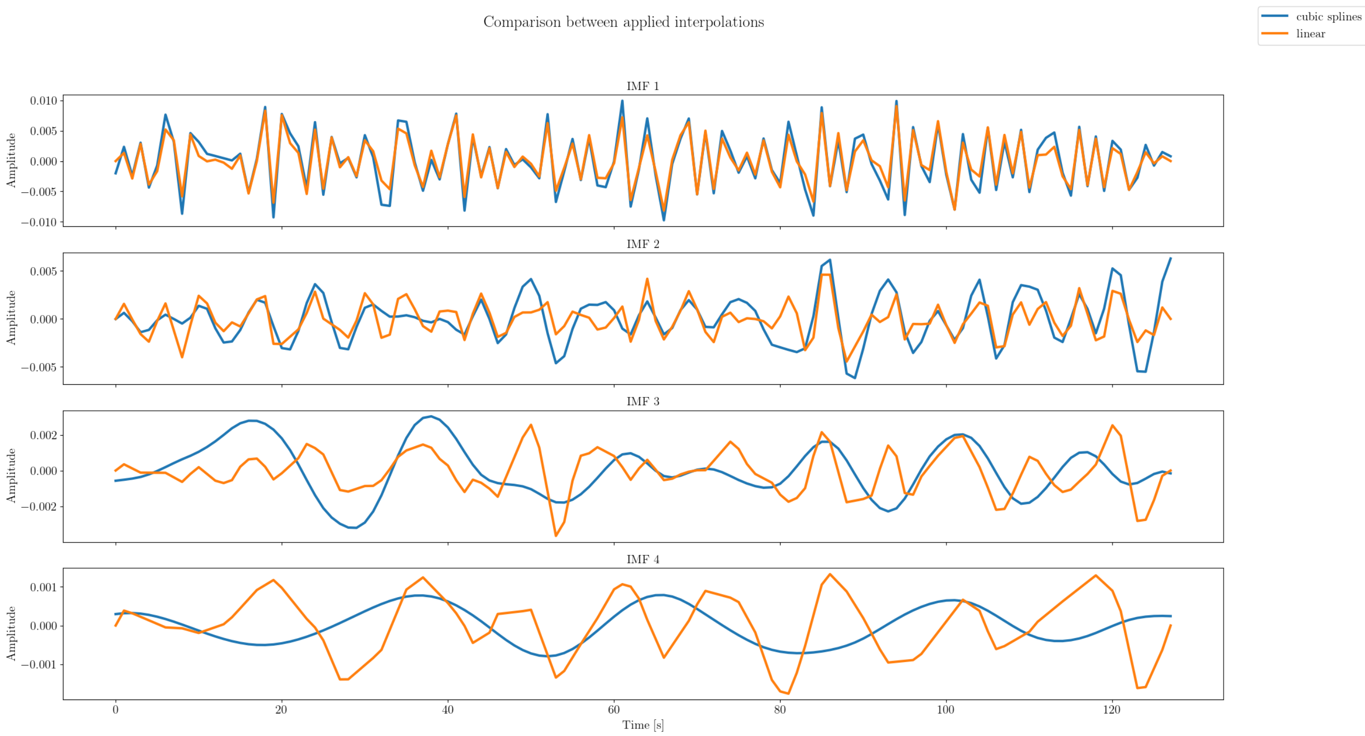

Fig. 3: Real part of the first four IMFs extracted from a QPSK modulation. In blue using a cubic spline and in orange using linear interpolation

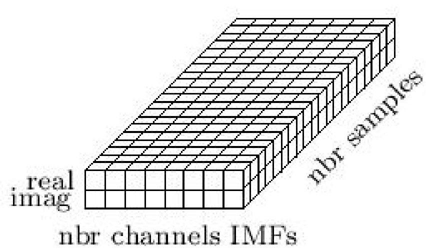

Fig. 4: 3D data shape, IMFs are stored in channels

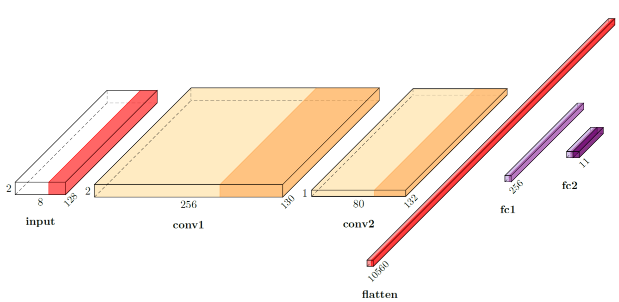

Fig. 5: CNN architecture applied in the case of a 3D data shape input

Also, for the same parameters, using a linear interpolation

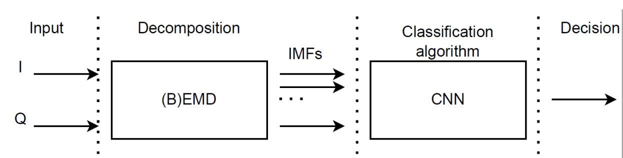

Fig. 6: Information flow

divides by two the required computation time.

Despite its potential benefits, linear interpolation does not result in a noticeable improvement in processing time compared to cubic spline interpolation, for a given threshold of classification accuracy. In practice, to achieve the same level of accuracy as cubic spline interpolation, it is necessary to increase the number of projections when using linear interpolation, which ultimately eliminates any potential time advantage.

Moreover, it has been found out that using linear interpolation increases the number of extracted IMFs.

V. Conclusion

Our results, as shown in Table 1, indicate that increasing the number of sifts and projections does not significantly affect the output accuracy of the classifier. This is an encouraging conclusion as it suggests that additional computation time is not needed to improve classification accuracy.

Upon analyzing the trade-off between decomposition time and classification accuracy, it is not recommended to utilize linear interpolation for envelope estimation in this specific use case. The reason for this is that linear interpolation does not provide sufficient accuracy compared to other methods of interpolation. Therefore, the accuracy of the classification results may be compromised if linear interpolation is employed for envelope estimation.

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References

[1] Yann LeCun, Y. Bengio, and Geoffrey Hinton. Deep learning. *Nature*, 521:436–44, 05 2015.

[2] Alexander Gros, Veronique Moeyaert, and Patrice Megret. Joint use of bivariate empirical mode decomposition and convolutional neural networks for automatic modulation recognition. In *2022 IEEE 33rd Annual International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC)*, pages 957–962, 2022.

[3] Timothy O'Shea and Nathan West. Radio machine learning dataset generation with gnu radio. *Proceedings of the GNU Radio Conference*, 1(1), 2016.

[4] Timothy James O'Shea, Tamoghna Roy, and T. Charles Clancy. Over-the-air deep learning based radio signal classification. *IEEE Journal of Selected Topics in Signal Processing*, 12(1):168–179, 2018.

[5] Sreeraj Rajendran, Wannes Meert, Domenico Giustiniano, Vincent Lenders, and Sofie Pollin. Deep learning models for wireless signal classification with distributed low-cost spectrum sensors. *IEEE Transactions on Cognitive Communications and Networking*, 4(3):433–445, 2018.

[6] Chad Spooner. An analysis of deepsig's 2016.10a data set. https://cyclostationary.blog/2020/04/29/all-bpsk-signals/. Accessed: 14.04.2022.

[7] Gabriel Rilling, Patrick Flandrin, Paulo Goncalves, and Jonathan M. Lilly. Bivariate empirical mode decomposition. *IEEE Signal Processing Letters*, 14(12):936–939, 2007.

[8] Norden Huang, Zheng Shen, Steven Long, M.L.C. Wu, Hsing Shih, Quanan Zheng, Nai-Chyuan Yen, Chi-Chao Tung, and Henry 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*, 454:903–995, 03 1998.

[9] Haris Iqbal. Harisiqbal88/plotneuralnet v1.0.0, December 2018.

[10] Yung-Hung Wang, Chien-Hung Yeh, Hsu-Wen Vincent Young, Kun Hu, and Men-Tzung Lo. On the computational complexity of the empirical mode decomposition algorithm. *Physica A: Statistical Mechanics and its Applications*, 400:159–167, 2014.

[11] Julien Fleureau, Amar Kachenoura, Jean-Claude Nunes, Laurent Albera, and Lotfi Senhadji. 3A-EMD: A Generalized Approach for Monovariate and Multivariate EMD. In *Information Sciences, Signal Processing and their Applications*, pages 300 – 303, Kuala Lumpur, Malaysia, May 2010.