Review of “A Hidden Markov Model Block-Thresholding Technique” (ASMB-21-231)

Using HMM to cluster wavelet coefficients in the proposed HMCV procedure is an interesting

idea. The algorithm itself is a minor extension of the CV-based block-thresholding works by Cai

(1999), Nason (1996), and McGinnity et al. (2017).

Major Comments.

1. The case for the HMM clustering method to perform better under non-Gaussian errors was

made solely by 4 simulated signals and 2 non-Gaussian distributions. Is there any theoretical

argument suggesting that the HMM model should be expected to outperform the competition

in non-Gaussian cases? For example, under what conditions the HMM model offers better

clusters for the wavelet coefficients?

The interdependencies between wavelet coefficients are often considered independent. However, for non-gaussian problems Crouse et al found that considering the interdependencies among wavelet coefficients improves thresholding. In this paper, we assume that wavelet coefficients have similar interdependencies which can be used to increase the effectiveness of thresholding. In this paper, we generate block threshold values for groups of interdependent wavelet coefficients using hidden Markov models for wavelet coefficient grouping. Similarly to the findings of Crouse we increase the effectiveness of our block thresholding scheme.

The HMM model offers better clusters for wavelet coefficients following a non-Gaussian distribution. This is shown in the examples of the 4 simulated signals.

Crouse, M.S., Nowak, R.D. and Baraniuk, R.G., 1998. Wavelet-based statistical signal processing using hidden Markov models. *IEEE Transactions on signal processing*, *46*(4), pp.886-902.

2. The HMM method (last two sentences on page 5 and step 4 on page 8) was not described

with sufficient detail. For example, what is the time index and the observation vector when

apply the HMM to the blocks of wavelet coefficients created by Cai (1999)?

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\cite{RabJuang1986} presents a coin flip example, shown in figure \ref{fig: tbc}, which can be modeled by HMMs. The observable outcome is a heads or a tail, and the hidden process is whether the coin flipped was biased towards head or biased towards tails. In this research, wavelet coefficients are modeled by HMM in the same way. The observed process is the magnitude and pattern of the wavelet coefficient blocks. The hidden process is the distribution of the wavelet coefficient blocks, whether they represent noise or signal.

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\Use the EM Baum-Welsh algorithm to fit the blocks of wavelet coefficients to an $n$ hidden Markov State. In this paper, $n = 2$, is used with the hmmlearn package, found at \url{https://github.com/hmmlearn/hmmlearn}. The exact meaning for the two states are unknown, but similar blocks of wavelet coefficients are grouped together in the same hidden state. The optimal definition is that blocks of wavelet coefficients containing mostly noise are grouped together in one state and blocks of wavelet coefficients containing mostly signal are grouped together in the other state.

3. To help practitioners, the computational complexity in comparison with the competition

should also be considered.

Minor Comments.

1. McGinnity (2017) was listed twice in the reference.

Corrected