

Figure 5. The feature maps of CNNs (top) and WaveCNets (bottom).

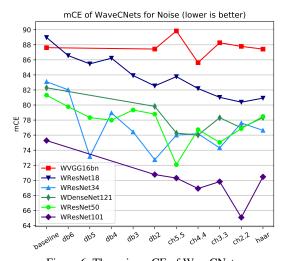


Figure 6. The noise mCE of WaveCNets.

4.2. Noise-robustness

In [15], the authors corrupt the ImageNet validation set using 15 visual corruptions with five severity levels, to create ImageNet-C and test the robustness of ImageNet-trained classifiers to the input corruptions. The 15 corruptions are sourced from four categories, i.e., noise (Gaussian noise, shot noise, impulse noise), blur (defocus blur, frosted glass blur, motion blur, zoom blur), weather (snow, frost, fog,

brightness), and digital (contrast, elastic, pixelate, JPEG-compression). $E_{s,c}^f$ denotes the top-1 error of a trained classifier f on corruption type c at severity level s. The authors present the Corruption Error CE_c^f , computed with

$$CE_c^f = \sum_{s=1}^5 E_{s,c}^f / \sum_{s=1}^5 E_{s,c}^{AlexNet} ,$$
 (17)

to evaluate the performance of a trained classifier f. In Eq. (17), the authors normalize the error using the top-1 error of AlexNet [19] to adjust the difference of various corruptions.

In this section, we use the poise part (750K images 50K)

In this section, we use the noise part (750K images, 50K \times 3 \times 5) of ImageNet-C and

$$mCE_{noise}^{f} = \frac{1}{3} \left(CE_{Gaussian}^{f} + CE_{shot}^{f} + CE_{impulse}^{f} \right)$$
 (18)

to evaluate the noise-robustness of WaveCNet f.

We test the top-1 errors of WaveCNets and AlexNet on each noise corruption type c at each level of severity s, when WaveCNets and AlexNet are trained on the clean ImageNet training set. Then, we compute mCE $_{\rm noise}^{\rm WaveCNet}$ according to Eqs. (17) and (18). In Fig. 6, we show the noise mCEs of WaveCNets for different network architectures and various wavelets. The "baseline" corresponds to the noise mCEs of original CNN architectures, while "dbx", "chx.y" and "haar" correspond to the mCEs of WaveCNets with different wavelets. Except VGG16bn, our method