An Image Sharpening Technique Based on Dilated Filters and 2D-DWT Image Fusion

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Abstract: Image sharpening techniques are pivotal in image processing, serving to accentuate the contrast between darker and lighter regions in images. Building upon prior research that highlights the advantages of dilated kernels in edge detection algorithms, our study introduces a multi-level dilatation wavelet scheme. This novel approach to Unsharp Masking involves processing the input image through a low-pass filter with varying dilatation factors, followed by wavelet fusion. The visual outcomes of this method demonstrate marked improvements in image quality, notably enhancing details without introducing any undesirable crisping effects. Given the absence of a universally accepted index for optimal image sharpness in current literature, we have employed a range of metrics to evaluate the effectiveness of our proposed technique.

1 INTRODUCTION

Image enhancement encompasses various techniques aimed at improving the quality, clarity, and perceptibility of images. Digital images often suffer from poor quality due to factors like inadequate contrast, undesirable shading, artifacts, or poor focus. Widely considered one of the most crucial techniques in image processing, image enhancement aims to improve the quality and visual appearance of an image. Numerous techniques have been developed and these are reviewed in (Archana and Aishwarya, 2016) and (Qi et al., 2021).

Unsharp Masking (UM) (Ramponi and Polesel, 1998) is a well-established technique for sharpening images that relies on subtracting a blurred version of the image from the original. Variants of UM, as discussed in (Polesel et al., 2000), control feature enhancement in specific areas of the image. In (Bilcu and Vehvilainen, 2008), UM is combined with sigma filters to simultaneously highlight noise reduction and edge enhancement. Furthermore, a generalized framework for UM is proposed in (Deng, 2010), which combines blocks for edge-preserving filters, contrast enhancement, and adaptive gain control.

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Contrast enhancement is crucial in many applications for highlighting image features. A classical method for achieving this is histogram equalization (HE) (Jain et al., 1995), which involves adjusting the grey levels of an image to achieve a uniform distribution of pixel values. Various variants of this method exist, such as the sub-regions HE analyzed in (Ibrahim and Kong, 2009), which partitions the input image and smoothens intensity values. In (Somal, 2020), the UM technique is applied to an image before implementing the HE technique.

The usage of dilated filters in image sharpening algorithms was proposed in (Orhei and Vasiu, 2022) and extended in (Orhei, 2022) or (Orhei and Vasiu, 2023). The extended spatial domain of the kernels has improved the performance of basic and complex enhancement algorithms.

The two-dimensional Discrete Wavelet Transform (2D-DWT) is a powerful algorithm for image enhancement, leveraging the wavelet theory to analyze and process images in both spatial and frequency domains. This method involves decomposing an image into a set of wavelet coefficients, representing different levels of detail. These approach was experimented in algorithms proposed by (Demirel and Anbarjafari, 2011), (Papamarkou et al., 2014), and (Zafeiridis et al., 2016).

In recent years, the problem of image sharpening has been approached using Convolutional Neural

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Networks (CNNs). (Kinoshita and Kiya, 2019) defines a CNN architecture that utilizes local and global features for image sharpening. (Li et al., 2021) proposes a more complex progressive-recursive image enhancement network for low-light images.

In this paper, we present a novel multi-level dilation wavelet scheme designed to enhance details at various scales while being robust to noise and computationally efficient. Our sharpening algorithm processes the input image using a cluster of UM techniques with varying dilation factors, followed by post-processing through a wavelet fusion mechanism. The visual results obtained using our approach demonstrate clear enhancements in image quality.

The proposed algorithm analyzes the image at multiple scales by using dilated UM, which means it can effectively sharpen both subtle details and prominent features while being selective about what features to enhance. By using the wavelet transform, edge preservation and noise reduction are increased along with the enhancement process. The fusion process in the wavelet domain allows the algorithm to adaptively combine information from different scales and orientations.

This algorithm is designed to leverage the strengths of both UM and 2D-DWT, using dilation to capture more detailed information and wavelet fusion to effectively combine these details into a single, enhanced image. The fusion process is particularly significant as it determines the final quality and characteristics of the sharpened image.

2 METHODOLOGY

2.1 Linear Unsharp Masking

In classical (linear) UM the term 'unsharp' refers to the subtraction of a blurred image, which effectively enhances edges. This is described by Equation 1, where $I(x,y)$ is the original image, $I_{um}(x,y)$ the output image, I_{lpf} the result of computing I with a Low Pass Filter (LPF), I_{hpf} the result of computing I with a HPF, and λ is the positive scaling factor controlling the level of contrast enhancement. However, this approach has downsides, including high sensitivity to noise and unintended enhancements in high-contrast areas of the image (Ramponi and Polesel, 1998), (Polesel et al., 2000), (Deng, 2010).

$$\begin{aligned} I_{um}(x,y) &= I(x,y) + \lambda I_{hpf}(x,y) \\ &= I(x,y) + \lambda(I(x,y) - I_{lpf}(x,y)) \end{aligned} \tag{1}$$

For our work, we employ the standard Laplacian operator, defined by Equation 2.

$$\begin{aligned} I_{lpf}(x,y) = 4I(x,y) - I(x-1,y) - I(x+1,y) \\ - I(x,y-1) - I(x,y+1) \end{aligned} \tag{2}$$

2.2 Dilated Filters

In our approach, we utilize dilated filters, a technique presented in (Bogdan et al., 2020). The core concept is to leverage a larger neighborhood around a pixel to capture more information. This is achieved by inserting additional rows and columns into the kernels, which act as gaps and are assigned a value of 0.

Consider K as a 2-D kernel with dimensions $w \times h$, where h is the height and w is the width of the filter. Introducing a dilation factor d, we can construct a dilated kernel K' with dimensions $(2d+h) \times (2d+w)$, as described in Equation 3. The Kronecker delta function δ is used to selectively include elements from the original kernel K in K'. Specifically, δ ensures that only the elements at positions satisfying the dilation condition are retained from K, while all other positions are set to zero. This approach effectively expands the kernel, introducing 0 between the original kernel elements, as detailed in (Orhei and Vasiu, 2023) or (Orhei et al., 2021a).

$$\begin{aligned} K'(i,j) = & K(i/(d+1), j/(d+1)) \\ & \cdot \delta(i\%(d+1)) \cdot \delta(j\%(d+1)) \end{aligned} \tag{3}$$

The underlying hypothesis of the technique is that dilation, as opposed to expansion, covers a larger area in terms of pixel distance rather than pixel density. Thus, it incorporates more information without increasing the number of pixels. Using a dilated filter is akin to applying the original filter to a downscaled image, an experiment explored in (Orhei et al., 2020).

2.3 2D Discrete Wavelet Transform

The DWT has established itself as a prominent tool in signal processing and image processing with notable applications since Mallat's foundational work (Mallat, 1989), which introduced the concept of multi-resolution signal analysis based on wavelet decomposition. DWT is known for its ability to simultaneously process localizations for time and frequency across various pyramid levels of an image, a concept elaborated in (Acharya and Chakrabarti, 2006).

Consider $S_{j,k}$ as the scaling (approximation) coefficients and $W_{j,k}^{k}$ as the wavelet coefficients at scale j for a signal $f(t)$, where $k \in \{1,2,3\}$ corresponds to

Figure 1: Example of resulting images from dilated UM phase, left to right the dilated factor increases from 0 to 5.

the type of detail (horizontal, vertical, or diagonal), and v and u are indices for the rows and columns, respectively. The indices l and m are used for summation. In the context of 2D signal processing with orthonormal filters, these coefficients can be expressed as products of a LPF (h) and a HPF (g). The coefficients at scale j can be derived from the coefficients at the subsequent scale, $j+1$. The approximation coefficients are calculated using Equation 4 and 5.

$$S_{j,v,u} = \sum_{l}\sum_{m} h(l-2v)h(m-2u)S_{j+1,l,m} \tag{4}$$

$$W^{k}_{j,v,u} = \sum_{l}\sum_{m} filter_{type}(l-2v, m-2u)S_{j+1,l,m} \tag{5}$$

For our use case, we choose the Daubechies-4 (Db4) wavelets variant, which is one of the most popular (Daubechies, 1992).

2.4 Proposed UM

The UM algorithm we propose is based on multi-scale analysis and wavelet fusion, scheme was inspired from two distinct sharpening approaches. The first approach involves UM using dilated kernels, as presented in (Orhei and Vasiu, 2022), where the authors propose the use of kernel dilation techniques for an expanded scale factor. The second approach combines 2D-DWT with UM, as detailed in (Papamarkou et al., 2014). Here, the authors propose a 2D wavelet transform sharpening algorithm that varies the UM and incorporates an image fusion concept.

Our novel sharpening method, outlined in Algorithm 1 is divided into two stages. In the first stage, to exploit important image details, we process the initial image using UM with varying dilatation factors. In the second stage, the resulting sharpened images are aggregated through a wavelet fusion technique, producing the final enhanced image.

Our method adopts a multiscale approach designed to accentuate image information across various levels of abstraction by utilizing dilated filters at

Data: $original\_image$, $octaves$
Result: Processed image
for k *in* $octaves$ **do**
  $um\_res_k \leftarrow$ UM_dilated$(original_img, k)$
  $img\_coeff \leftarrow$ 2dwt(um_res_k)
end
$coeff\_fusion \leftarrow$ fusion_rule(img_coeff)
$i2dwt\_out \leftarrow$ i2dwt$(coeff_fusion)$
$img\_out \leftarrow$ normalize$(i2dwt_out)$

Algorithm 1: UM Dilated 2D-DWT Approach.

different dilation factors. This is evident in Figure 1, where each level of dilation reveals fewer details, albeit with a trade-off in increased artifact size and a potential over-crisp effect.

By integrating information from different dilation levels, referred to as octaves, our method places greater emphasis on the dominant features in the image that are accentuated by dilation. However, caution is necessary regarding the number of octaves used to avoid an undesirable state of over-crisping.

The second stage of our method introduces a wavelet fusion technique that enhances the sharpening features processed in the first stage. This fusion process aims to integrate features from the set of processed images to create a single, improved image. The decision to use wavelet fusion is driven by its proven effectiveness in the spatial domain, as demonstrated in various applications.

As defined in Algorithm 1, the final block in our process is fusion. The aggregation rule applied here is crucial for determining the optimal combination of different coefficients to produce the best output image. In this context, we have explored various fusion rules, detailed below. In these rules, I_F represents the fused image, and $D_{I_F}(x)$ denotes the 2D-DWT coefficient for image location x:

1. Maximum Fusion Rule (UM_P_MAX):

$$D_{I_F}(x) = \max(|D_{I_0}|(x), |D_{I_1}|(x), \ldots, |D_{I_n}|(x)) \tag{6}$$

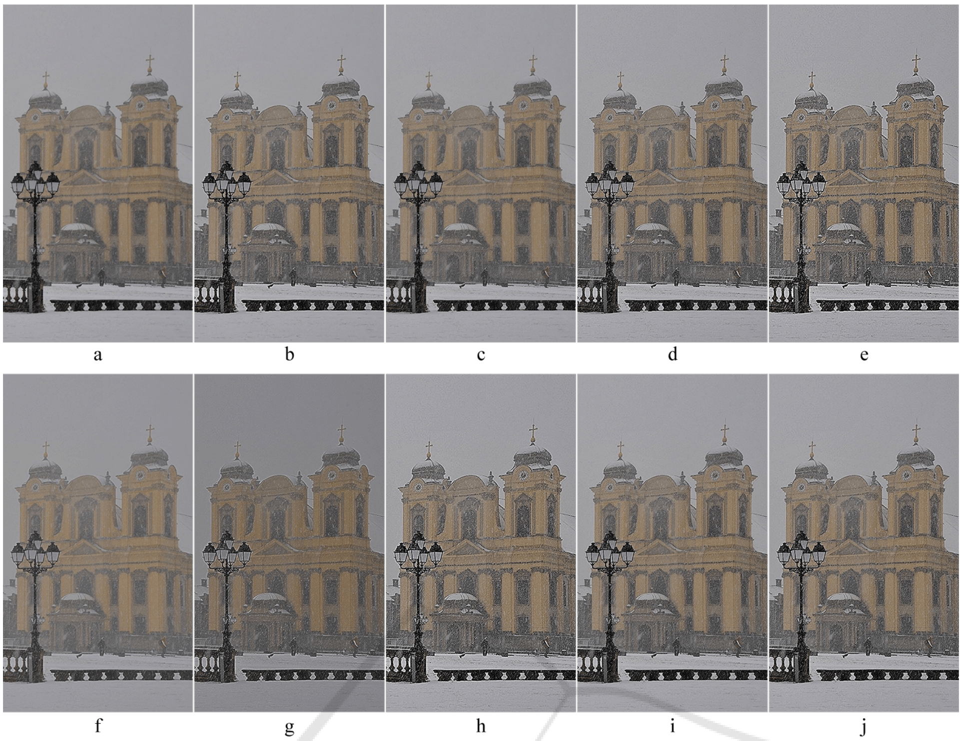

Figure 2: Results on 00109 image: (a) Original image; (b) UM_STD; (c) UM_STD_LAP; (d) UM_5D; (e) UM_7D (f) UM_2DWT (g) UM_P_MAX; (h) $UM\_P\_AVG\_1$; (i) $UM\_P\_AVG\_2$; (j) $UM\_P\_AVG\_3$.

2. Direct Proportional with dilation Average Rule ($UM\_P\_AVG\_1$):

$$D_{I_F}(x) = \frac{\sum_{k=0}^{n} k \cdot D_{I_k}(x)}{n} \tag{7}$$

3. Inverse Proportional with dilation Average Rule ($UM\_P\_AVG\_2$):

$$D_{I_F}(x) = \frac{\sum_{k=0}^{n} (n-k) \cdot D_{I_k}(x)}{n} \tag{8}$$

4. Average Rule ($UM\_P\_AVG\_3$):

$$D_{I_F}(x) = \frac{\sum_{k=0}^{n} D_{I_k}(x)}{n} \tag{9}$$

The integration step in the fusion process is crucial for the performance of the dilated filter. Image fusion has become a significant operation in image processing, particularly when combined with multi-scale analysis. Wavelet-based techniques are widely recognized as the most effective for image fusion, having been successfully implemented in numerous applications. Their ability to seamlessly blend features from multiple images makes them an ideal choice.

2.5 Evaluation Metrics

Evaluating the sharpening quality is challenging due to the lack of objective measures for image quality or sharpness, so we will evaluate several metrics.

Entropy (H), it serves as a measure of uncertainty, rising as disorder increases. In other words, an increase in H corresponds to an augmentation in the level of details.

Spatial Frequency (SF), which expresses the overall activity level in an image, is defined by Equation 10, where RF is the row frequency (Equation 11) and CF is the column frequency (Equation 12), where $M \times N$ image block F with grey values.

$$SF = \sqrt{(RF)^2 + (CF)^2} \tag{10}$$

$$RF = \sqrt{\frac{1}{MN} \sum_{m=1}^{M} \sum_{n=2}^{N} [F(m,n) - F(m,n-1)]^2} \tag{11}$$

$$CF = \sqrt{\frac{1}{MN} \sum_{n=1}^{N} \sum_{m=2}^{M} [F(m,n) - F(m-1,n)]^2} \tag{12}$$

Root Mean Square Contrast ($RMSC$), a pixel-based metric where higher values indicate better contrast, is presented in Equation 13 (where $M \times N$ is the dimensions of image F and $\overline{F}$ is the mean intensity).

$$RMSC = \sqrt{\frac{1}{MN} \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} (F(m,n) - \overline{F})^2} \tag{13}$$

The Blind/Referenceless Image Spatial Quality Evaluator ($BRISQUE$), is a non-reference image quality assessment metric that operates in the spatial domain. It evaluates up to 18 statistical features across two image scales, contributing to distortion evaluation and quality verification through a two-stage classification algorithm (Mittal et al., 2012).

3 RESULTS

In this section, we present the results obtained using the proposed approach, as described in Section 2. Our approach introduces four distinct fusion rules for the UM algorithm, as detailed in Equations 6 up to 9.

To evaluate the effectiveness of our proposed algorithm variants, we compare them against the classical UM method (Ramponi and Polesel, 1998) (UM_STD) and using la Laplace kernel (UM_STD_LAP); the dilated UM approach (Orhei and Vasiu, 2022) (UM_5D and UM_7D); the 2D-DWT technique from (Papamarkou et al., 2014) (UM_2DWT).

Our evaluation is two-fold. First, we use a small dataset extracted from TMBuD (Orhei et al., 2021c). This initial evaluation aims to provide a focused analysis of the algorithms' performance in diverse scenarios. Second, we extend our evaluation to the entire TMBuD dataset, which allows us to observe metric trends across a significant number of scenarios and gain a comprehensive understanding of the effectiveness in a broader context.

In the scope of reproducible research, we used for our simulations EECVF - End-to-End Computer Vision Framework - (Orhei et al., 2021b), a Python open-source solution that aims to support researchers. The experiments done in this paper can be reproduced by running $main\_dilated\_2dwt\_sharpening\_dilated.py$ module.

3.1 Small Dataset

In Figure 3, we showcase the images selected for our small dataset analysis. This dataset comprises 10 images, each representing a unique challenge commonly encountered in real-life photography scenarios. Notably, the dataset includes images captured in low-light conditions (figures 00005 and 00511), adverse weather conditions (figures 00109 and 07403). Additionally, the dataset encompasses images that are blurred, a common issue resulting from incorrect camera usage or the limitations of the capturing device. These diverse examples provide a comprehensive range of scenarios to effectively assess the performance of our proposed image processing techniques.

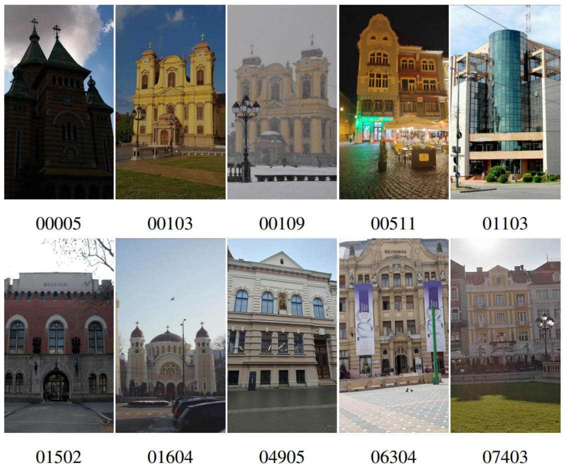

Figure 3: Small dataset used to evaluate created from TMBuD (Orhei et al., 2021c).

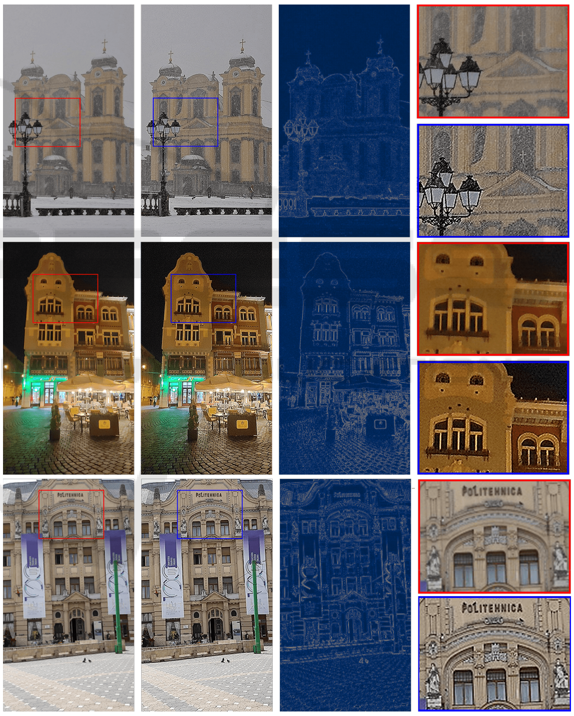

Figure 4: Proposed $UM\_P\_AVG\_1$ example where: (a) Original image; (b) Proposed UM result; (c) Difference between (a) and (b); (d) Zoom on (a); (e) Zoom on (b).

In Figure 2, we showcase the visual outcomes of the various sharpening algorithms evaluated, as previously outlined. However, it's important to note that in some instances, the sharpening process has led to an over-enhancement effect, akin to "burning" of the image. This is especially evident when examining images f and g in contrast to the others. Another interesting aspect observed is the benefit that dilation brings, particularly evident in images d, e, and h to

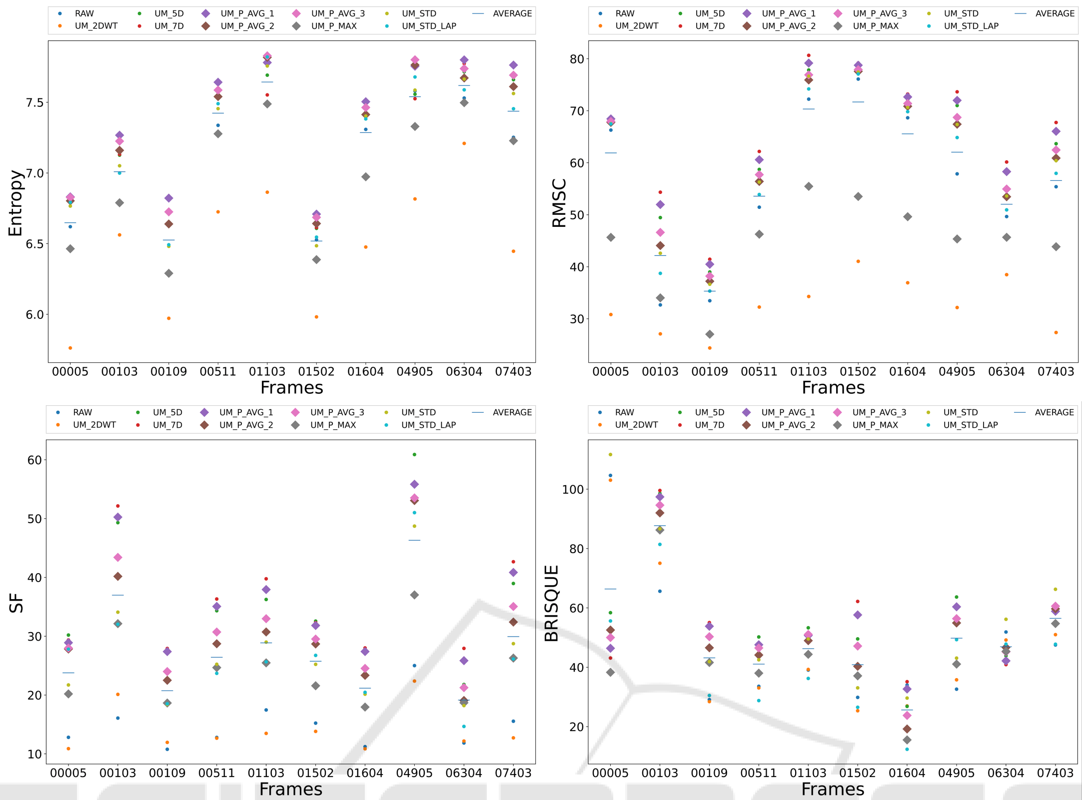

Figure 5: H, $RMSC$, SF and $BRISQUE$ metrics on the small dataset.

j, in terms of contrast enhancement. This enhancement is especially apparent in the computation of the weighted average, as demonstrated in $UM\_P\_AVG\_1$.

In Figure 4, we observe the enhanced results achieved by applying our proposed UM algorithm with the direct proportional average fusion rule, as defined in Equation 7. Specifically, in the zoomed-in sections of the original image (Figure 4 *d*) and the sharpened image (Figure 4 *e*), enhancements are evident in areas such as the text on top the building and the contours of the windows and wall ornaments.

In Figure 5, the outcomes of the H, SF, $RMSC$, and $BRISQUE$ metrics on the small dataset are presented. An analysis of these results indicates that the proposed UM algorithms, particularly those utilizing average fusion rules, exhibit a slight overshooting across all evaluation methods, with a pronounced effect in the H assessment. Conversely, the UM algorithm employing the maximum fusion rule (UM_P_MAX) demonstrates values closer to the median in the H and SF evaluations, and slightly below the median for $RMSC$. Notably, the UM algorithms using the inverse proportional average rule ($UM\_P\_AVG\_2$) and the simple average rule ($UM\_P\_AVG\_3$) show comparable results in the $RMSC$ and SF metrics, indicating a consistency in their performance across these evaluation methods.

Further insights can be drawn from Figure 5. The average fusion rule-based methods ($UM\_P\_AVG\_1$, $UM\_P\_AVG\_2$, $UM\_P\_AVG\_3$) show elevated H values, suggesting an increase in information content or image variability. This could indicate enhanced image details but may also imply the introduction of noise. In terms of SF, the dilated UM variants (UM_5D and UM_7D), along with $UM\_P\_AVG\_1$, demonstrate the highest values, indicating a marked improvement in image sharpness and edge definition. The $RMSC$ results align with SF findings, where the dilated UM methods and $UM\_P\_AVG\_1$ score highest, implying enhanced image contrast. However, this contrast enhancement could potentially lead to the overemphasis of features or noise. Conversely, the $BRISQUE$ scores reveal that the dilated UM methods, especially UM_7D, and $UM\_P\_AVG\_1$ method, enhance perceived image quality compared to the original.

3.2 TMBuD Dataset

Encouraged by the promising results achieved with the smaller dataset, we are now motivated to expand our analysis to encompass the entire TMBuD dataset, which comprises a substantial collection of 1120 im-

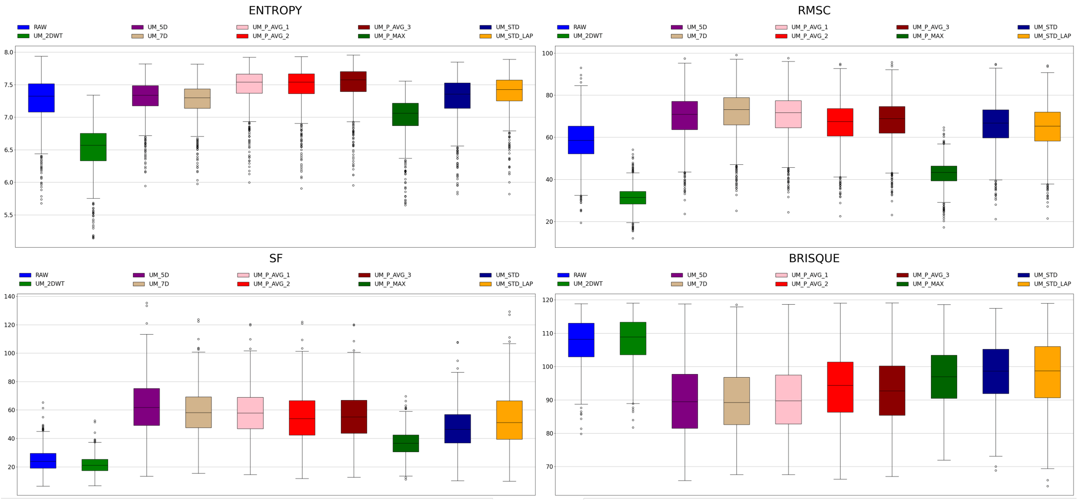

Figure 6: H, $RMSC$, SF and $BRISQUE$ metrics on the entire TMBuD dataset.

ages. This dataset is an excellent choice for further evaluation due to its diverse range of conditions represented in the images and the fact that all images were captured using mobile devices.

For a better visibility of the results on the entire TMBUD dataset evaluation is presented in Figure 6. A notable observation is the prevalence of outliers in the H metric, even among the original images. This trend suggests the presence of images with comparatively lower information content within the dataset. Such a characteristic could be attributed to images having more uniform pixel distributions, repetitive textures, or a dominance of similar objects across the dataset. This hypothesis is further supported by the presence of low outliers in the $RMSC$ evaluation, indicating a subset of images with lower contrast. Interestingly, the lack of a significant number of outliers in the $BRISQUE$ metric suggests that these characteristics are inherent to the images themselves, rather than being a result of the applied algorithms. This observation underscores the importance of considering the intrinsic properties of images when evaluating the performance of image processing techniques.

The proposed methods utilizing average fusion rules, specifically $UM\_P\_AVG\_1$, $UM\_P\_AVG\_2$, and $UM\_P\_AVG\_3$, consistently show the highest H values. This suggests they are particularly effective in introducing additional information or variability into the images, potentially enhancing detail. However, this enhancement might come with the trade-off of increased noise. In contrast, the original image and the dilated UM with dilatation 2 (UM_7D) maintain H values close to the original, indicating a more conservative approach.

In terms of SF and $RMSC$, the dilated UM methods (UM_5D and UM_7D) and the proposed $UM\_P\_AVG\_1$ method stand out with significantly higher values. These results suggest a substantial enhancement in image sharpness, edge definition, and contrast, which are crucial for visual clarity and detail perception.

The $BRISQUE$ scores, which provide a measure of image quality without reference, further complement these findings. The lower $BRISQUE$ scores for the dilated UM methods, particularly UM_7D, and the $UM\_P\_AVG\_1$ method suggest an improvement in perceived image quality compared to the original. This aligns with their higher SF and $RMSC$ values, indicating that these methods not only enhance sharpness and contrast but also do so in a way that is generally perceived as an improvement in image quality.

In summary, the proposed methods with average fusion rules generally enhance image details and contrast more aggressively than other methods, as indicated by higher H, SF, and $RMSC$ values. However, this might come at the cost of potentially introducing noise. The dilated UM methods also show strong performance in enhancing image quality, particularly in terms of sharpness and perceived quality.

4 CONCLUSIONS AND FUTURE WORK

In this paper we proposed an image sharpening technique that integrates wavelet fusion with multiple dilated UM algorithms. This approach stands out for its computational efficiency without compromise the quality of image enhancement.

The performance metrics for our proposed approach align with our initial hypothesis, images processed with our algorithm exhibit improved sharpness while avoiding common issues such as overshooting or introduction of noticeable artifacts.

The proposed UM algorithms utilizing average fusion rules (especially $UM\_P\_AVG\_1$) demonstrated considerable performance both in a smaller dataset and across a more extensive dataset.

Despite the sophisticated processing involved, wavelet transforms are computationally efficient, and multiscale analysis can be performed quickly.

As future work we might consider other fusion rules and also other multi-scale fusion methods, such as a pyramidal approach in order to enhance the results of the image sharpening.

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