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Abstract—Compression noise reduction is similar to the super-resolution problem in terms of the restoration of lost high-frequency information. Because learning-based approaches have proven successful in the past in terms of addressing the super-resolution problem, we focus on a learning-based technique for compressed image denoising. In this process, it is important to search for the exact prior in a training set. The proposed method utilizes two different databases (i.e., a noisy and a denoised database), which work together in a complementary way. The denoised images from the dual databases are combined into a final denoised one. Additionally, the input noisy image is decomposed into structure and texture components, and only the latter is denoised because most noise tends to exist within the texture component. Experimental results show that the proposed method can reduce compression noise while reconstructing the original information that was lost in the compression process, especially for texture regions.

Index Terms—compression noise, learning-based denoising, dual learning, texture domain

I. INTRODUCTION

IMAGE compression is essential due to storage constraints, limited communication bandwidth, and real-time transmission demands. The use of lossy compression has been popular as a method to achieve higher compression ratios. When using typical image compression standards such as JPEG and H.264, the amount of information is reduced through coarse quantization in the DCT domain. However, this inevitably leads to image quality degradation such as ringing and blocking artifacts [1]–[3].

As the target compression ratio increases, the DCT coefficients of the image signals are quantized more coarsely. This leads to ringing artifacts near the edge and the over-smoothing of the original high frequency signals. These compression artifacts are dependent on the characteristics of the original signal. Motivated by these observations, we attempt to understand the close relationship between compression noise and the original image signal, and learned priors are utilized in the effective reduction of compression artifacts.

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Several compression artifact reduction methods have been proposed in the literature. Most existing methods can be classified as filtering [4]–[11], iterative [12]–[15], or maximum a posteriori (MAP) estimation [16] approaches. Filtering methods adaptively smooth out block edges and ringing noise while preserving image edges. They have been used on spatial [4]–[7], transform [8, 9], and texture [10, 11] components within an image. In particular, blocking artifacts can be separated into texture or high frequency components using image decomposition in order to preserve most of the original visual detail. Iterative approaches [12]–[14] are typically based on the theory of projections onto convex sets (POCS), and iterative non-linear filtering has been proposed. The MAP-based approach [16] exploits maximum likelihood parameter estimation to reduce ringing artifacts.

Compression artifacts can also be reduced by common denoising methods such as non-local means (NLM) [17], block matching 3D (BM3D) [18], and steering kernel regression (SKR) [19]. We found that they also exhibit excellent artifact reduction performance over a wide range of experiments.

However, as with exclusive compression noise reduction methods, there are still fundamental performance limits to denoising methods, such as blurring, incomplete reconstruction of the original information, and insufficient noise removal.

In compression noise reduction, there are two key goals: removing visual artifacts incurred by the compression process and accurately recovering the original information lost in the compression process. From this perspective, it is expected that a learning-based approach would be particularly suitable. In recent years, learning-based denoising methods [20]–[22] have been proposed in the literature, and this work is a straightforward extension of these methods to deliver further denoising improvement.

In previous learning-based methods, an input noisy patch is searched for in an example database (DB) that contains pairs of noisy and original patches. Once several similar patches have been found, the ultimate denoised patch is obtained by applying locally linear embedding (LLE) between the noisy and original patches. In this paper, we extend the previous work in two ways. First, the noisy image is decomposed into both structure and texture components, and the proposed denoising algorithm is applied only to the texture component. This is why most compression noise is classified as textural. By denoising the texture information only, we can avoid the degradation (e.g., blurring) of the original signal structure (e.g., the edge), which is unavoidable in common denoising techniques. Second, we

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