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***Abstract*—In this paper, we propose a new learning based joint Super-Resolution (SR) and denoising algorithm for noisy images. The individual processing of denoising and SR when super-resolving a noisy image has drawbacks such as noise amplification, blurring and SR performance reduction. In the proposed joint method, principal component analysis (PCA) based denoising is closely combined with a self-learning SR framework in order to minimize the SR visual quality degradation caused by noise. Experimental results show that the joint method achieves an SR image quality improvement in terms of noise and blurring, when compared with the state-of-the-art joint method and sequential combinations of individual denoisng and SR.**

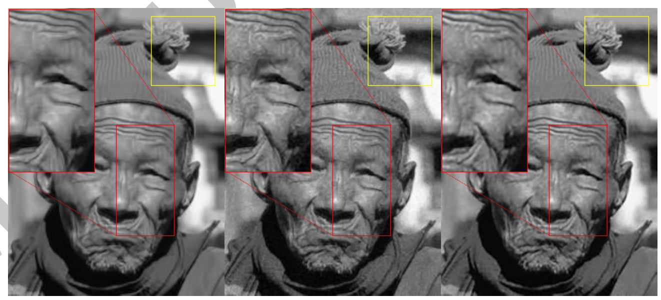
***Index Terms*— Self-learning, image super-resolution, PCA, denoising, noisy image**

1. Introduction

As mobile devices become increasingly equipped with cameras, image and video contents are copiously generated and popularly shared through the Internet. Those contents are commonly produced by non-expert users with relatively low-end cameras, and thus likely to be of a low visual quality and frequently suffer from noise. Particularly as the era of UHD-resolution displays has already begun, these contents need to be improved in terms of spatial resolution.

In the field of spatial resolution enhancement, super-resolution (SR) algorithms have been studied widely [1-5]. Self-similarity refers to the observation that, in natural images, small patches often occur in a repetitive manner within the original scale and across different scales, and this phenomenon has been commonly exploited for SR. Commonly, self-similarity based SR approaches search for patches similar to a target patch in a self-image, and reconstruct its lost high frequency component from those similar examples [6-9].

These SR algorithms primarily aim to enhance the spatial resolution of a clean image, rather than a noisy one. However, in practical application, noisy images are commonly encountered. If a low resolution noisy image is up-scaled to a higher resolution through learning based SR, the visual quality of the up-scaled image appears severely degraded compared to the clean version. For learning based SR processes, it is important to find the best prior in a training set. However, since noises limits the ability to find the best prior, it is quite probable that the high frequency (HF) of the similar patches discovered differs from that of the original target patch.



(a) NR-SR (b) SR-NR (c) joint NR and SR

Fig. 1. Subjective quality comparisons of *Old-man.*

Thus, to find the best prior when super-resolving a noisy image, the super-resolution process should be accompanied by denoising such as [10-13]. Commonly, there are two approaches to incorporating denoising in super-resolution: pre-processing and post-processing. The former means that denoising is followed by SR sequentially. One important drawback of typical denoising methods from the SR perspective is that they not only remove target noises but also inevitably degrade the original data. For example, most of state-of-the-art denoising methods have the side-effect of blurring or over-smoothing, which is particularly observable at weak texture regions in natural images. The other drawback is that complete noise removal is highly challenging; weak noise not outstandingly visible on the low resolution (LR) domain may persist. Such noise is considerably amplified by SR, and may lead to severe artifacts on the HR domain. On the other hand, in the post-processing method denoising occurs after SR. The noise in an input LR image is significantly amplified by the SR process and it is much harder to remove this boosted noise. In the post-processing denoising step, this boosted noise may be regarded as original information rather than pure noise. In addition, since the super-resolved image contains much more pixels than the input LR, the computational load required for denoising increases considerably. The drawbacks of pre-