Limitations when Improving Security Camera Video

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Abstract—Security is one of the most important things in our daily lives and the security business is a big industry. Security cameras are set in many areas in order to keep us safe. When a crime occurs, we often hear that police analyze the security camera footage. It takes long time and it is often the case that the footage is not helpful in the investigation at all. The reason is very simple. Many of the security camera images do not have sufficient resolution. Currently there are many super resolution (SR) technologies. In detective dramas technicians solve crimes using SR technologies turning blurry images taken with a security camera into sharp high resolution ones with a click of a button. However, in real life it is not so easy. In this paper we discuss the current issues and limitations of the SR technologies.

Keywords—Super Resolution; Motion Blur; Video; Image, Nonlinear Signal Processing;

1 Introduction

Due to the semiconductor's technology advance video cameras are now small in size and very affordable. The photo/video technology impacts our daily life since most people have mobile phones with a built-in digital camera. This also brings the security industry to a whole new level. We are now surrounded by security cameras in downtowns, airports, stations and other places. However, when a crime happens, security cameras often fail to do the job well. Since the important information is often contained in a small part of the video, we need to enlarge that part. The enlargement always causes blur. The blurry images are often unreadable and therefore rendered useless. In the past criminal's confessions were a crucial part when solving crimes. Currently police investigations are shifting from the confessions to the objective evidence, such as the security camera video. As mentioned earlier, it often happens that a crime caught on a security camera cannot be used since the video did not work well due to the enlargement blur. In detective TV dramas and films we often see a police technician improving resolution of the blurry images in order to find the information they are looking for. However, such technologies do not exist. Although super resolution (SR) technologies are good candidates, they are not practical due to several reasons. In this paper the quality of security camera videos and the limitations of the SR for this application are discussed.

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2 Image Quality Improvement

The security camera footages come with several issues such as resolution, coding distortion, contrast, brightness and others. Among them the resolution is the most common problem. The area of interest is usually a small part of the whole image. It is often the case that those small parts need to be enlarged which inevitably causes the enlargement blur. Enhancers have been used to improve the image quality [1] [2]. Such enhancers, however, cannot actually improve the resolution, since they only amplify the edges in the image. It means that the high frequency elements in the image are enhanced for viewers to get the feeling that the resolution of the image has improved. In contrast, to actually improve the resolution, it is necessary to create high-frequency elements that the original video does not have. Since the enlarged security camera images do not have high frequency elements to be amplified, the enhancer does not work for them.

2.1 Super Resolution

Recently, new signal processing methods that are different from the enhancer have been developed. These methods fall under the title of Super Resolution (SR). Among SR technologies Super Resolution Image Reconstruction (SRR) [3] [4] [5] [6] [7] [8] [9] [10] [11] [12] [13] [14]. and Learning Based Super Resolution (LBSR) [15] [16] are the typical ones. Blind deconvolution (BD) is another approach for restoring an out of focus image. It has been mostly used in astronomy [17] [18] [19]. Image restoration techniques are categorized in image restoration field. However, BD works for blurry images and improves resolution. Recently, BD has been categorized as SR [20]. In this section these SR technologies.

2.2 SRR

Figure 1 shows the basic idea of SRR [21]. The first step is to process the HRI with a low pass filter (LPF). The cut-off frequency of the LPF is higher than the Nyquist frequency of the LRIs. LRIs are created from HRI with sub-sampling and all LRIs have aliasing. All LRIs are distinct since the sampled pixel phases of each LRI are different. The summation of sampled pixels exceeds the pixels in the HRI. For example, suppose we want to make 256×256 pixel LRIs from 512×512 pixel HRI. In this case, four LRIs would have the same pixels as the HRI; however, SRR must create more than four 256×256 images to reconstruct HRI. That is, we need a larger amount of information than is in the HRI in order to reconstruct it with SRR. The LRIs are thus composed by iterations, minimizing the cost function to recreate the HRI. Using the latter part of the SRR signal processing, we may create HRI if we have many LRIs. In practical situations we have only one image to create HRI. It is rare to use SRR for practice.

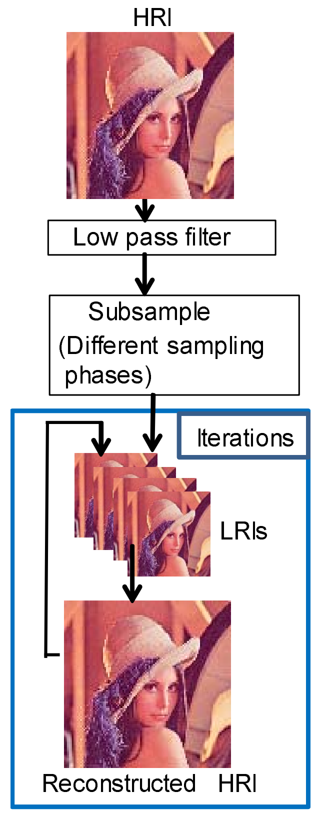

Fig. 1. SRR algorithm

2.3 LBSR

Figure 2 shows the LBSR block diagram. LBSR works with an image database that is shown in the center of Figure 2. The left image is the input (LRI) and the right image is the output (HRI). During the process of LBSR the database is used to improve the resolution of the input image. The similar images are found and their high resolution sharp edges are used to improve the input image resolution. Practically the blurry edges in the input image are replaced by the sharp edges from the database images. This process is repeated and many similar images are referred to compose HRI using iterations. However, even though we construct a huge database, there might be a

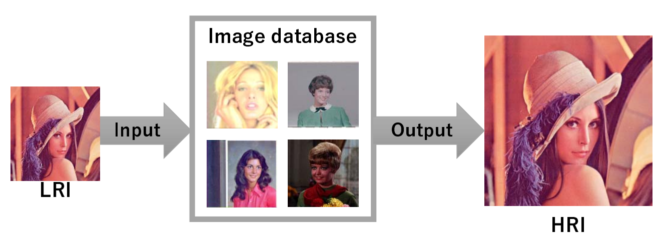

Fig. 2. LBSR algorithm

case that very similar images might have slight differences rendering them usable. It means that the performance of LBSR has limitations [22].

3 BD

3.1 BD algorithm

When we capture an image of an object, we capture the beams of light that are reflected on the surface of the object. After being reflected, the beams are diffracted, diffused, and/or reflected in the space and lens of the camera until they reach the imaging device in the camera. These factors degrade resolution and make the images blurry. Here we define $\psi(x,y)$ as the true image and $\phi(x,y)$ as the observed blurry image. (x,y) denotes the two dimensional vector. The relationship between $\psi(x,y)$ and $\phi(x,y)$ [23] [19] can be presented as follows.

$$\phi(x,y) = \int\int \psi(\xi,\eta)P(x-\xi,y-\eta)d\xi d\eta \tag{1}$$

$$\psi(x,y) = \int\int \phi(\xi,\eta)Q(x-\xi,y-\eta)d\xi d\eta \tag{2}$$

Here, $P(\cdot,\cdot)$ is the blur factor and $Q(\cdot,\cdot)$ is the inverse filter of $P(\cdot,\cdot)$ [23]. $P(\cdot,\cdot)$ is called the spread function (PSF) and generally it has a Gaussian shape characteristic [23]. These are filtering processes between $\phi(x,y)$ and $p(x,y)$.

The blurry image can be restored by finding $P(x,y)$. Since this is a typical inverse problem, it is impossible to solve it using a direct method [24]. Instead, of a direct method, an iterative method is proposed. Lucy, 1974 showed that $\phi(x,y)$ can be obtained as follows. Using the Bayesian inference, we obtain the following equation.

$$Q^r(x-\xi,y-\eta) = \frac{P^r(x-\xi,y-\eta)\psi^r(x,y)}{\phi^r(x,y)} \tag{3}$$

Here r is the iteration number. In Equation (2), $\phi(\xi,\eta)$ is the original blurry image and we define it as $\phi^0(\xi,\eta)$ as the initial image.

Plugging Equation (3) into Equation (2), we obtain the following formula.

$$\begin{aligned}\psi^{r+1}&(x,y)\\ &= \int\int \psi^r(x,y)\frac{\phi^0(x,y)}{\phi^r(x,y)}P^r(x-\xi,y-\eta)d\xi d\eta\\ &= \psi^r(x,y)\int\int \frac{\phi^0(x,y)}{\phi^r(x,y)}P^r(x-\xi,y-\eta)d\xi d\eta \end{aligned}\tag{4}$$

Here, we transform Equation (1) with the iteration number r.

$$\phi^r(x,y) = \int\int \psi^r(x-\xi,y-\eta)P^r(\xi,\eta)d\xi d\eta \tag{5}$$

Using Equation (3), we also obtain the recursion equation of r about PSF,

$$\begin{aligned}P^{r+1}&(x,y)\\ &= P^r(x,y)\int\int \frac{\phi^0(x,y)}{\phi^r(x,y)}\psi^r(x-\xi,y-\eta)d\xi d\eta\end{aligned}\tag{6}$$

We define a scalar value $E(r)$ to evaluate the convergence.

$$E(r) = \int\int |\phi^r(x,y) - \phi^{r-1}(x,y)|dxdy \tag{7}$$

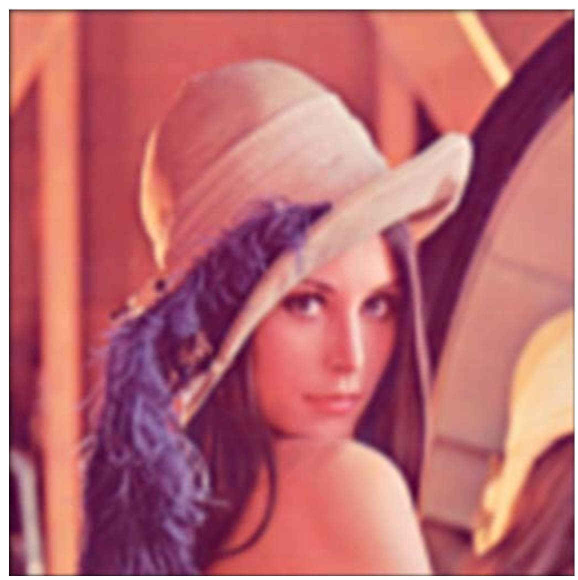

Fig. 3. Blurry image

Equation 7 is called L1 norm. Equation 7 is an indicator of the iterations process. It decreases during the convergence process.

Using the recursion Equations (4), (5), (6), Equation 7 and the iterations, we can obtain $\psi(x,y)$, HRI and $P(x,y)$, PSF. The algorithm is called the Lucy [19] and Richardson [18] algo-

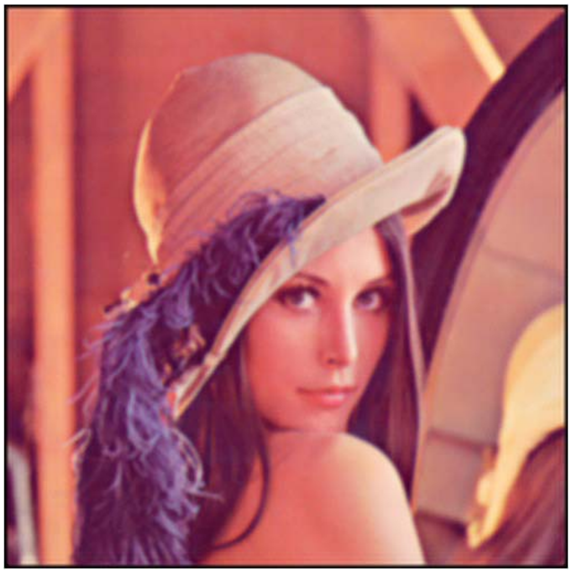

Fig. 4. Image processed with SRR

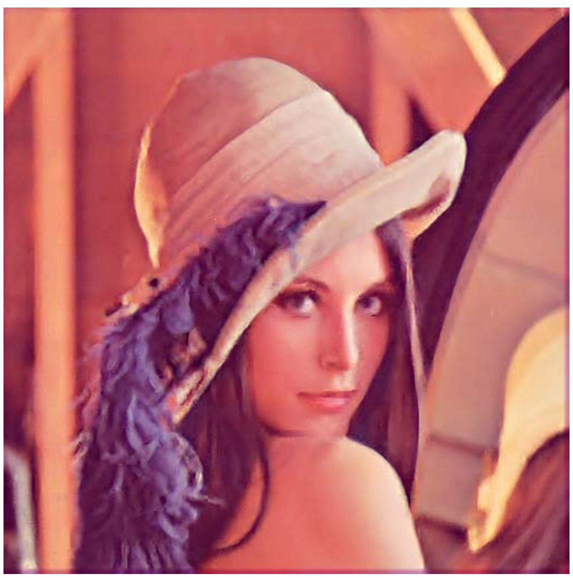

Fig. 5. Image processed with LBSR

rithm and it is used in astronomy to refocus images of planets star constellations.

3.2 Performance of SR technologies

In order to discuss the image quality improvement and image resolution it would have been good to evaluate the images with the actual image size because there is no resolution difference between a reduced blurry image and a reduced normal resolution image. However, due to the space limitation the images in this section were revised but we tried to keep them as big as possible. Figure 3 shows a blurry image. The original image of Figure 3 is called Lena/Lenna [25] and its resolution is 512×512. It is processed with the 15x15 Gaussian filter to make a blurry LRI. Figure 3 is processed with SRR, and the LBSR and BD results are shown in Figures 4, 5, and 6 respectively. Although the three processed images are improved when compared with Figure3, the images are not shown in their original sizes. Although the original resolution was 512×512, the images are reduced due to the size limitations. Figure 7 shows the enlarged part of Figures 3, 4, 5, and 6. We discuss the performance of SR based on Figure 7. The resolution of SRR, Figure 7(b), is worse than that of the other two images (Figures 7(c), (d)) especially on the eyelashes. Figure 7(c), LBSR image, has artifact around the nose area and under the right eye. Although LBSR and SRR are the typical SR technologies, their performance is worse than that of BD shown in Figure 7(d). In practice, security camera images are generally requested to be enlarged 16 times or the course of investigation. Such magnification can only exploit information from the small part of a security camera image. In this case the enlargement causes a lot more blur than that of Figure3. It means that the current SR technologies including BD do

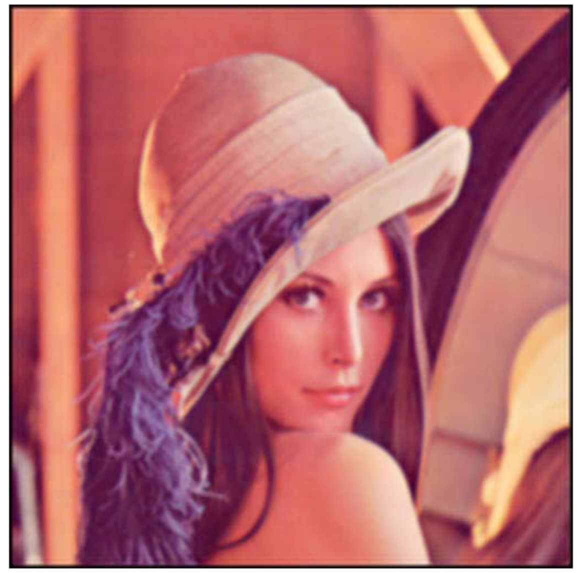

Fig. 6. Image processed with BD

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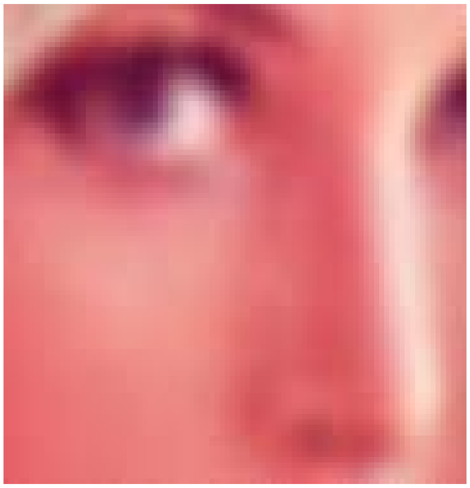
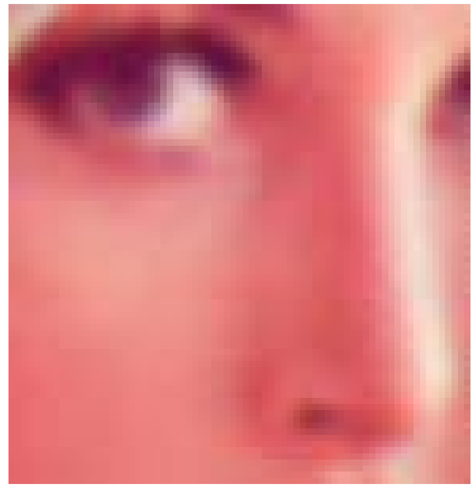
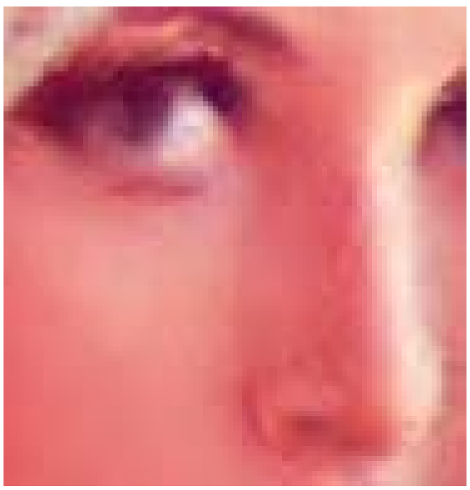


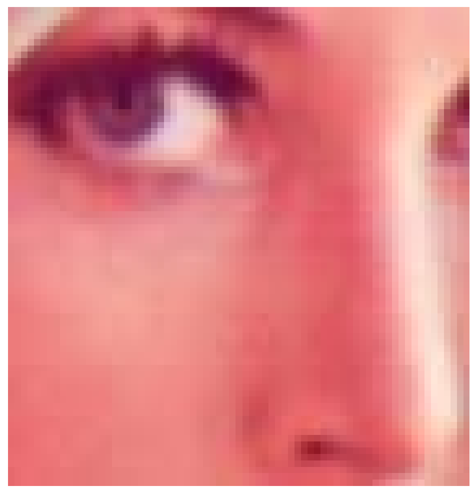
(a) Original



(b) SRR



(c) LBSR



(d) BD

Fig. 7. Comparison of three methods

not meet the current security industry requirements.

4 Conclusion

Nowadays the suspect's confession is not the only crucial evidence in court and the objective evidence is required by the judge. Although large areas are covered by security cameras, the important information is generally contained in the small part of the image and we need to enlarge that small part of the image. The enlargement inevitably causes blur. We do not have an effective technology to fix this problem. New ideas and technologies are wanted. In order to overcome this problem, I would like to see the involvement, participation and suggestions from many researchers.

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