Real-time Super Resolution Algorithm for Security Cameras

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Abstract: Security is one of the most important things in our daily lives. Security camera systems have been introduced to keep us safe in shops, airports, downtowns, and other public spaces. Security cameras have infrared imaging modes for low-light conditions. However, infrared imaging sensitivity is low, and the quality of images recorded in low-light conditions is often poor as they do not always possess sufficient contrast and resolution; thus, infrared imaging devices produce blurry monochrome images and videos. A real-time nonlinear signal processing technique that improves the contrast and resolution of low-contrast infrared images and video is proposed. The proposed algorithm can be installed in a field programmable array.

1 INTRODUCTION

Because of the increasing demand for security and the decreasing cost of security cameras, the security camera systems are expected to be worth four billion USD in 2015. Analog security cameras are being replaced by digital devices, and Internet protocol (IP) security camera systems are becoming increasingly common. Security camera systems are not stand alone systems; they usually work in conjunction with network technology. In TV detective dramas, investigators sometimes have special imaging technologies that can create high-resolution images (HRI) from blurry images. Unfortunately, in reality such technologies do not exist; therefore, increasing the resolution of the imaging devices is the only method to obtain HRIs.

In recent times, high-resolution 4K cameras have become more affordable, and networked 4K security camera systems have also become available. Such systems record videos onto servers. IP security systems are commonly employed with central building control systems and at large-scale events. Although high resolution security camera systems are becoming increasingly convenient and are widely used, they still do not function effectively in low-light conditions. During the night, lighting conditions are insufficient and security cameras are switched to infrared mode, which provides only low-resolution and low-contrast images. Several methods have been proposed to improve infrared images (Lee et al., 2012; Ibekwe et al., 2012; Pflugfelder et al., 2005). However, they are unable to produce images of sufficiently high quality for their intended application.

Interest in super resolution (SR) technology, which attempts to improve image resolution, has grown rapidly in recent times (Farsiu et al., 2004; Park et al., 2003; Katsaggelos et al., 2010; van Eekeren et al., 2010). However, most SR technologies consider only still images, and such studies have focused primarily on the signal processing of color images shot under adequate lighting conditions. Although the algorithms for still images have been applied to infrared images (Farsiu et al., 2004; van Eekeren et al., 2010), the image quality produced by such methods remains insufficient.

Another important requirement for security cameras is real-time signal processing (note that most SR algorithms are complex and non-real time systems). At a crime scene, time is very valuable; thus, signal processing speed is very important. SR algorithms that perform iterations or require several low-resolution images (LRI) cannot process video in real time; thus, the time required to perform these processes can impede criminal investigations. Therefore, to address this problem, SR processing should be performed in real time.

An SR algorithm for infrared images that satisfies both image quality and processing speed has not been reported to date. In recent times, a processing method that uses nonlinear signal processing (NLSP) to improve resolution by creating higher frequency elements has been proposed (Gohshi, 2014). However, this method does not satisfy the requirements for infrared images. In this study, we have attempted to modify the NLSP method (Gohshi, 2014) to significantly improve the quality of infrared images.

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The remainder of this paper is organized as follows. In Section 2, the definition and limitations of SR technologies are discussed. Section 3 introduces the NLSP algorithm. In Section 4, a real-time SR algorithm and expanded NLSP for a security camera system are proposed. Section 5 presents experimental results, and conclusions and suggestions for future work are given in Section 6.

2 SUPER RESOLUTION

Improving image resolution from analog TV to HDTV has been a highly active field of research for more than two decades. Note that many images cannot be recorded under reasonable conditions because of optical limitations, such as different lenses, lighting conditions, and focus. As a result, such images do not always have sufficient resolution. For years, unsharp masking (USM; also referred to as edge enhancement) has been the only method to enhance video in real-time systems. Although USM is a simple and cost effective method, it does not essentially improve resolution; it provides better image quality using either a band-pass filter (BPF) or a high-pass filter (HPF). However, USM can introduce noise and edges to images.

SR technology, which has been researched for approximately two decades (Elad and Feuer, 1996), creates an HRI from LRIs. Many SR methods have been proposed (Farsiu et al., 2004; Park et al., 2003; van Eekeren et al., 2010; Matsumoto and Ida, 2008) ; however, these methods are primarily applied to still images, where processing time is not of paramount importance. Such algorithms perform iterations to construct an HRI from LRIs. These iterations continue until the value calculated by a constraint condition converges to the minimum value. Minimizing this constraint condition is simply a method of weighted least squares, and the reached point is generally not exact. Furthermore, there is no guarantee that the minimum point can create the highest resolution. In such methods, the number of iterations can become greater than 200 (Sugie and Gohshi, 2013) , and the iterations are sometimes discontinued before they converge to the minimum point. Even though such methods can reach the highest resolution, the required iterations create a bottleneck for real-time signal processing. Moreover, to assess results, previous studies have only visually compared the original and the SR processed images. However, this is a subjective quality assessment.

It is almost impossible to recognize the difference between the proposed SR technologies and previous image enhancement technologies by simply assessing the pre- and post-processed images because the validities of image processing methods differ depending on the images. In recent times, some manufacturers have stated that their commercial products are equipped with SR functions. However, these manufacturers have not disclosed the SR algorithms they employ, and there is no evidence to support their claims. Therefore, an objective assessment method is required.

SR can be defined as creating high-frequency elements that the original image does not possess. Here we propose to compare the two-dimensional fast Fourier transform (2D-FFT) of the preprocessed image with that of the post-processed image. If the 2D-FFT results are shown, we can compare the spectra of the pre- and post-processed images. If the spectra of the SR post-processed image have high-frequency elements that the preprocessed image does not possess, it can be concluded that the signal processing method has expanded the spectra. If a proposed SR technology could create high-frequency elements that the original image does not possess, the 2D-FFT results should be demonstrated. Thus, we propose 2D-FFT results as an objective assessment criteria for SR.

Figure 1 shows a crisp image and Figure 2 shows a blurred image of Figure 1. Figure 3 is the 2D-FFT result of Figure 1, and Figure 4 is the 2D-FFT result of Figure 2.

By comparing Figures 3 and 4, it can be seen that the resolution of Figures 1 and 2 can be assessed quantitatively. Since images have different characteristics, the validity of SR differs depending on the images. Thus, only comparing the pre- and post-processed images is an ineffective way to assess the validity of SR because this is a qualitative subjective assessment; thus, scores may vary for different observers. However, the proposed 2D-FFT criterion provides an objective assessment that yields quantitative scores.

3 NONLINEAR SIGNAL PROCESSING

NLSP has been proposed for the up-conversion of 4K video to 8K video (Gohshi, 2014). Although the NLSP algorithm (Figure 6) is quite simple, it can create higher frequency elements that the original image does not possess.

The input image is distributed to a HPF and an adder (ADD). The HPF detects edges in the image, and the edges are processed with a nonlinear function (NLF). The NLF is a symmetry function with respect to the original point of the coordinate where the ordinate and abscissa cross. The cubic function $y = x^3$ is an example that satisfies this condition. The edges detected with the HPF are processed with this cubic function.

Figure 1: Original image.

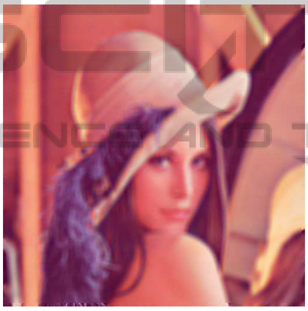


Figure 2: Blurred image of Figure 1.

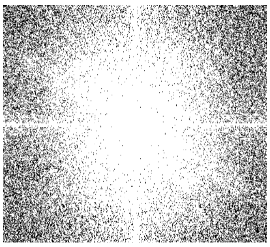


Figure 3: 2D-FFT result of Figure 1.

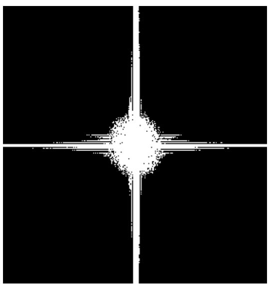


Figure 4: 2D-FFT result of Figure 2.

The cubic function can create high-frequency elements that the input image does not possess. Note that an image expanded by a Fourier series comprises sine and cosine functions with the fundamental frequency of the image ω_0. Here edges are represented with $\sin(n\omega_0)$ and $\cos(n\omega_0)$ functions. Here, n is an integer number ($n = 0, \pm 1, \pm 2, \cdots$). Here $y = x^3$ generates $\sin^3(n\omega_0)$ and $\cos^3(n\omega_0)$. Note that $\sin^3(n\omega_0)$ can be rewritten with $\sin(3n\omega_0)$and $\cos^3(n\omega_0)$ can be rewritten with $\cos(3n\omega_0)$. This implies that frequency elements that have a frequency three times higher than that of the original image can be generated, and these high-frequency elements are edges that the original image does not possess. The edges are added to the input image by the ADD, and the resulting HRI is obtained. Although there are many SR technologies that use LRIs, NLSP uses only a single LRI as input.

If an even function is selected, such as $y = x^2$, the positive or negative sign information is lost, and the NLF output becomes positive. However, edges are either positive or negative. The most significant bit is separated from the edge information before the NLF is performed and is then restored after the NLF. With this method, we can use even NLFs. In this method, for $x \geq 0$, $y = x^2$ is selected, and for $x < 0$, $y = -x^2$ is selected. This method allows much more flexibility than the algorithm shown in Figure 6 because the choice of NLF is expanded.

Figure 5 shows an image processed with NLSP. Figure 5(a) is an enlargement from HDTV to 4K. Figure 5(b) shows the NLSP processed result of Figure 5(a). Although Figure 5(a) is blurry, Figure 5(b) is clearly superior to Figure 5(a). Figures 5(c) and 5(d) are the 2D-FFT results of Figures 5(a) and 5(a) respectively. Note that Figure 5(d) has horizontal and vertical high-frequency elements that Figure 5(c) does not possess. Although NLSP was applied to infrared images, the signal processing shown in Figure 6 does not produce an infrared image of sufficiently high quality. To improve the infrared image quality, a new NLSP method is proposed in the next section.

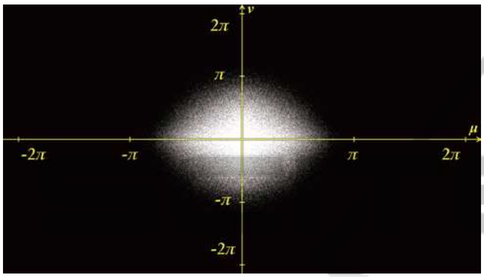
4 SIGNAL PROCESSING TECHNIQUE FOR SECURITY CAMERAS

Infrared images are low-contrast monochrome images that do not have high-frequency elements. Figures 8 and 10 are typical infrared images. Note that they lack contrast and do not demonstrate high-frequency elements. Simply adjusting the characteristics of the HPF (Figure 6) cannot generate edges.

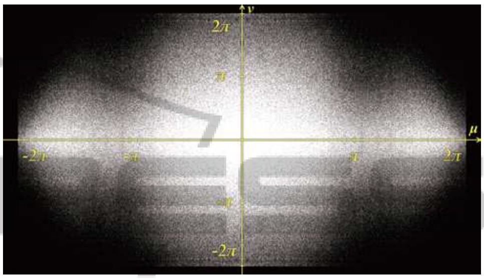
Thus, an algorithm for infrared images (Figure 7) is proposed to handle low-contrast images and edge detection. Note that the contrast should be adjusted

(a) 4K image enlarged from HD

(b) Figure 5(a) with NLSP



(c) 2D-FFT result of Figure 5(a)



(d) 2D-FFT result of Figure 5(b)

Figure 5: Image processed with real-time NLSP.

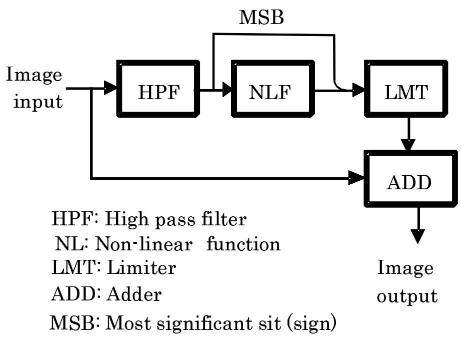


Figure 6: NLSP algorithm.

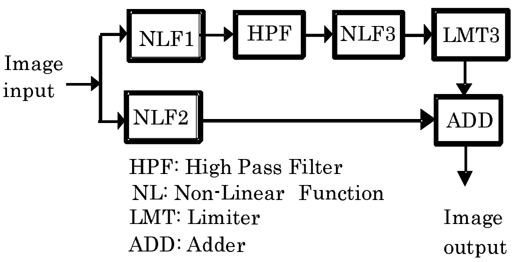


Figure 7: Block diagram of signal processing for infrared image.

prior to performing NLSP. In Figure 7 three NLFs (NLF1, NLF2 and NLF3) are employed. In the upper path, NLF1 changes the contrast to create more high-frequency elements than the algorithm shown in Figure 6. Using NLF1, edges at low-luminance levels are amplified so that the HPF can easily detect them. NLF3 has nonlinear characteristics and functions that are similar to the NLF shown in Figure 6. NLF2 is employed for infrared images to create high contrast for a low-contrast image. NLF1, NLF2 and NLF3 produce high-contrast images. To increase contrast, NLF1 and NLF2 should be convex downward. By using several characteristics of NLFs for NLF1 and NLF2, $y = x^{0.3}$ was selected for our experiments. In addition, $y = x^3$ was selected for NLF3 for the experiments. Here, x is the input, and y is the output of NLF1, NLF2 and NLF3. However, more experiments for NLF1, NLF2 and NLF3 are required to produce improved infrared image quality.

5 EXPERIMENT AND DISCUSSION

As is shown in Figures 9 and 11, the algorithm shown in Figure 7 to process the input image shown in Figures 8 and 10 improves the contrast and details of the image. Although these infrared images were shot outside under very similar lighting conditions, the processed images show much more information. Images processed with (Gohshi, 2014) are shown in Figures 12 and 13 for the comparison between the conventional method and the proposed method.

Figure 8: House (before processing).

Figure 9: House (after processing).

Figure 10: Deer (before processing).

Figure 11: House (after processing).

Figure 12: House (Figure 8 Processed with (Gohshi, 2014).

Figure 13: House (Figure 10 Processed with (Gohshi, 2014).

In these experiments, NLF1 and NLF2 were set to $y = x^{0.3}$ and NLF3 was set to $y = x^3$to assess the basic functionality of the proposed method. The processed results shown in Figures 9 and 11 can be improved by modifying the NLFs. It was observed that the proposed technique can improve infrared image quality. However, to produce a practical system, further research is required to compare the NLFs of the algorithm, i.e., NLF1 and NLF2. Although NLF3 must go through the original point in the coordinates, NLF2 can employ $y = x^3 + a$ a to adjust brightness. Here, the luminance signal is positive, and the parameter a can make the image clearer with appropriate adjustment. It is also necessary to adjust other characteristics, such as the HPF characteristics (i.e., filter tap length and coefficients).

Our eyes function as an LPF in dark environments and as a BPF in bright environments. Research results on NLSP techniques are limited despite the fact that our eyes work as a nonlinear system. Further research of such NLFs is required to improve image quality. The proposed method can allow security cameras to capture important images with high quality using simple real-time hardware. In recent times, the security camera industry changes stand-alone security camera and its recording system and IP camera systems have been introduced. We expect that the proposed method can be used to develop more cost-effective and useful IP camera systems.

6 CONCLUSIONS

A single image SR technique for infrared images has been proposed. Many SR technologies have been proposed; however, to date, no objective SR assessment method has been available. Thus, we have proposed 2D-FFT to evaluate SR technologies objectively. Infrared images are low-resolution and have low-contrast. Although the proposed algorithm is simple, it can improve the quality of such images. The proposed SR technique can improve contrast and can create higher frequency elements that the original image does not possess. We expect that the proposed algorithm can be used to develop real-time capable hardware for video and image content. The proposed method increases the potential of security systems at night ; however, further research into the proposed algorithm and nonlinear functions is required for a practical security camera system.

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