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Restoration of Automated Video Enhancement in Image Processing

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ABSTRACT

The new approach is proposed in this paper capable of restoring a single high-quality image from a given image sequence distorted by atmospheric turbulence To correct geometric distortion and reduce space and time-varying blur, This approach reduces the space and time-varying deblurring problem to a shift invariant one. Next, a temporal regression process is carried out to produce an image from the registered frames, which can be viewed as being convolved with a space invariant near-diffraction-limited blur. Blind deconvolution problems arise in many image restoration applications. Most available blind deconvolution methods are iterative. A novel non-iterative blind deconvolution method. Finally, contrast enhancement is applied. We further propose a learning-based metric specifically for image quality assessment in the presence of atmospheric distortion. A novel non-iterative blind deconvolution algorithm is implemented to remove diffraction-limited blur from the fused image to generate the final output. Experiments using controlled and real data illustrate that this approach is capable of alleviating geometric deformation and space-time varying blur caused by turbulence, recovering unprecedented details of the scene and significantly improving visual quality.

Key Words : High Quality image, Blind Deconvolution, Visual Quality

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INTRODUCTION

An image may be considered to contain sub-images sometimes referred to as regions-of-interest, ROIs, or simply regions. This concept reflects the fact that images frequently contain collections of objects each of which can be the basis for a region. In a sophisticated image processing system it should be possible to apply specific image processing operations to selected regions. Thus one part of an image (region) might be processed to suppress motion blur while another part might be processed to improve color rendition. Sequence of image processing. Most usually, image processing systems require that the images be available in digitized form, that is, arrays of finite length binary words. For digitization, the given Image is sampled on a discrete grid and each sample or pixel is quantized using a finite number of bits[5]. The digitized image is processed by a computer. To displsay a digital image, it is first converted into analog signal, which is scanned onto a display. Closely related to image processing are computer graphics and computer vision. In computer graphics, images are manually made from physical models of objects, environments, and lighting, instead of being acquired (via imaging devices such as cameras) from natural scenes, as in most animated movies. Computer vision, on the other hand, is often considered high-level image processing out of which a machine/computer/software intends to decipher the physical contents of an image or a sequence of images (e.g., videos or 3D full-body magnetic resonance scans). In modern sciences and technologies, images also gain much broader scopes due to the ever growing importance of scientific visualization (of often large-scale complex scientific/experimental data). Examples include microarray data in genetic research, or real-time multi-asset portfolio trading in finance. Before going to processing an image, it is converted into a digital form. Digitization includes sampling of image and quantization of sampled values. After converting the image into bit information, processing is performed. This processing technique may be, Image enhancement, Image restoration, and Image compression. Many image processing and analysis techniques have been developed to aid the interpretation of remote sensing images and to extract as much information as possible from the images. The choice of specific techniques or algorithms to use depends on the goals of each individual project. In this section, we will examine some procedures commonly used in analyzing/interpreting remote sensing images. Prior to data analysis, initial processing on the raw data is usually carried out to correct for any distortion due to the characteristics of the imaging system and imaging conditions. Depending on the user's requirement, some standard correction procedures may be carried out by the ground station operators before the data is delivered to the end-user. These procedures include radiometric correction to correct for uneven sensor response over the whole image and geometric correction to correct for geometric distortion due to Earth's rotation and other imaging conditions (such as oblique viewing). The image may also be transformed to conform to a specific map projection system. Furthermore, if accurate geographical location of an area on the image needs to be known, ground control points (GCP's) are used to register the image to a precise map (geo-referencing).

Image processing is a method to convert an image into digital form and perform some operations on it, in order to get an enhanced image or to extract some useful information from it. It is a type of signal dispensation in which input is image, like video frame or photograph and output may be image or characteristics associated with that image. Usually Image Processing system includes treating images as two dimensional signals while applying already set signal processing methods to them. It is among rapidly growing technologies today, with its applications in various aspects of a business. Image Processing forms core research area within engineering and computer science disciplines too. In order to aid visual interpretation, visual appearance of the objects in the image can be improved by image enhancement techniques such as grey level stretching to improve the contrast and spatial filtering for enhancing the edges.
Image fusion is the process of combining relevant information from two or more images into a single image. The resulting image will be more informative than any of the input images. In remote sensing applications; the increasing availability of space borne sensors gives a motivation for different image fusion algorithms. Several situations in image processing require high spatial and high spectral resolution in a single image. Most of the available equipment is not capable of providing such data convincingly. The image fusion techniques allow the integration of different information sources. The fused image can have complementary spatial and spectral resolution characteristics. However, the standard image fusion techniques can distort the spectral information of the multispectral data while merging. In satellite imaging, two types of images are available. The panchromatic image acquired by satellites is transmitted with the maximum resolution available and the multispectral data are transmitted with coarser resolution. This will usually be two or four times lower. At the receiver station, the panchromatic image is merged with the multispectral data to

convey more information. Many methods exist to perform image fusion.

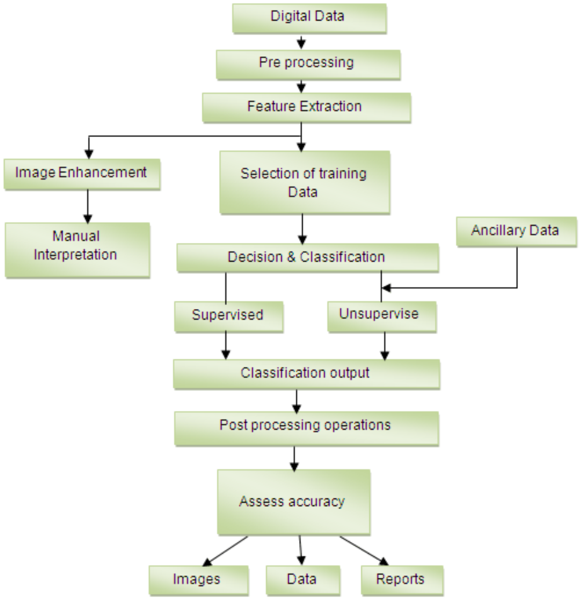

Fig 1: Overview of image processing

MATERIALS AND METHODS

Image quality assessment is used to measure perceived image degradation, typically compared to an ideal or perfect image. This is important when assessing the performance of individual systems or for comparing different solutions. Image quality metrics can be classified according to the availability of a reference (distortion-free) image, with which the distorted image is to be compared.

Next, a regression-based process is carried out to produce an image convolved with a near-diffraction-limited PSF, which can be viewed as spatially invariant. Finally, a blind deconvolution algorithm is implemented to remove diffraction-limited blur from the fused image to generate the final output. Experiments using controlled and real data illustrate that this approach is capable of alleviating geometric deformation and space-time varying blur caused by turbulence, recovering unprecedented details of the scene and significantly improving visual quality. In strong turbulence, not only scintillation, which produces small-scale intensity fluctuations in the scene and blurring effects are present in the video imagery, but also a shearing effect occurs and is perceived as different parts of objects moving in different directions. This effect is found at locations such as hot roads and deserts, as well as in the proximity of hot man-made objects such as aircraft jet exhausts. This is particularly a problem close to the ground in hot environments and can combine with other detrimental effects in long range surveillance applications, where images can be acquired over distances.

The displacement between the distorted objects in the successive frames may be too large for conventional image registration, using non-rigid deformation, to cope with. Equally, matching using feature detection is not suitable since strong gradients within each frame are randomly distorted spatially.

The very basic one is the high pass filtering technique. Later techniques are based on Discrete Wavelet Transform, uniform rational filter bank.

PROPOSED WORK

Novel Non-Iterative Blind Deconvolution Algorithm

2D image restoration of ground-based astronomical images. In practice, all blind deconvolution algorithms require some partial knowledge about the input or imaging process. If the blind deconvolution algorithm considered is iterative and depends on many unknowns, it is in some cases difficult to appreciate any advantages it provides compared to non-blind iterative algorithms, whereby the PSF can be estimated empirically. In the quest, here, for a deconvolution algorithm, Solar System imaging has been used as a test bed for a blind deconvolution algorithm that is non-iterative. Despite the number of unknowns in the blind algorithm, its results are comparable to many traditional algorithms. The advantage of getting a final result with a single iteration allows for a much more productive estimation of the blurring function. It is based on the assumption that the degradation function in the frequency domain is nonnegative non negative, smooth and slowly varying. This holds true for a number of degradations occurring in various imaging applications and especially blurring by atmospheric turbulence and some lens intrinsic aberration. True image can be modeled as

$$\mathbf{g(x; y) = h(x; y) \;\; f(x; y) + n(x; y);}$$

where (x; y) represents the discrete pixel coordinates of the image frame, g(x; y) is the blurred image, f (x; y) is the true image, h(x; y) is the point spread function (PSF), n(x; y) is the additive noise, and represents the discrete two-dimensional linear convolution operator. In this model, the observed image g(x; y), true image f (x; y) and noise n(x; y) are coupled linearly, so the problem of recovering f (x; y) from g(x; y) is referred to as the linear image restoration problem[1].The existing linear image restoration algorithms assume that the PSF is known a priori and attempt to invert it and reduce noise by using varying amounts of information about the PSF. Blind deconvolution, where both an original image and a blurring kernel are reconstructed from a blurred and noisy image, is a nonlinear and ill-posed image processing problem. Recently, classical methods for the regularization of non-blind deconvolution have been adapted to this problem. We investigate the behaviour of minimum norm solutions. Under certain applicable conditions, we prove existence as well as uniqueness and derive the explicit form of the minimum norm solution. This constitutes a nonlinear inversion operator for the blind deconvolution problem. The solution depends continuously on the given data provided that the data fulfil a weak smoothness condition. In a sense, blind deconvolution is less ill-posed than non-blind deconvolution. Given noisy data, this smoothness condition is no longer satisfied. We utilize Tikhonov regularization of a Sobolev embedding operator to restore smoothness, so that the inversion operator may be applied. We note that regularization and inversion are two separate tasks. We prove convergence of the regularized solution to the noise-free minimum norm solution and, when the noise-free data fulfil a stronger Sobolev smoothness condition, we give a convergence rate result. Our approach is non-iterative and thus very fast. It conserves mass and symmetry of the kernel and works robustly for a wide range of images and kernels. No knowledge of exact kernel shape and support size is necessary.

Figure 2: Novel Non-Iterative Blind image Deconvolution

Blind deconvolution is the recovery of a sharp version of a blurred image when the blur kernel or point spread function is unknown. Despite of exhaustive research over the last few decades, blind image deconvolution still remains an unsolved problem. In this paper, we present a novel morphology based initial estimation technique of true image for the Iterative Blind Deconvolution (IBD) of linearly degraded images without the explicit knowledge of either the original image or the point spread function[2]**.** The only constraints imposed are the non-negativity and finite support size of the true image. The restoration process involves Wiener filtering instead of usual inverse filtering in iterative loop. The filter coefficient β that depends on the noise level is also estimated mathematically taking pixel values of blurred image and its median filtered version into consideration. The conventional IBD with these twofold modifications is implemented and experimental results show satisfactory convergence, uniqueness and robustness.

Figure 3: Visual Approach of a given Algorithm

PROBLEMSTATEMENT

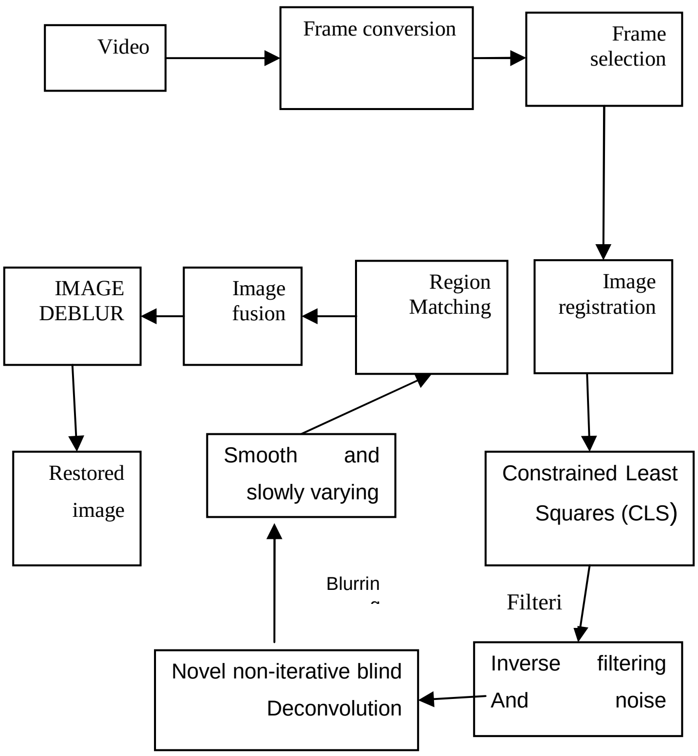

Figure 4: Overview of Video Enhancement Image Process

In this paper, a simple yet efficient algorithm for restoration of signals using a non-iterative blind deconvolution approach has been presented. It works for many image restoration cases whereby the blurring function is smooth and slowly varying. Many astronomical imaging cases suffer from this kind of degradation. The algorithm is further improved by adding the MTF of atmospheric turbulence into the formula making it optimized for a wide range of astronomical applications. The non-iterative nature of the algorithm and its computational simplicity enable convenient workflow to estimate various unknowns in a very short period of time. With the improved algorithm, a benchmark of 290 kpixels per second has been achieved on a desktop class iMac computer with 2.66 GHz Intel Core 2 Duo processor, restoring a 32-bit precision image. This results in a 1000x1000 pixels RGB image deconvolved in less than 4 seconds. Despite the fact that this paper is focused on astronomical imaging, the deconvolution algorithm presented can be used in a wide variety of other applications, for example, long range imaging, satellite imaging, aerial photography, photo radar ticketing devices, ground cameras tracking rocket launches, microscopy and many more[2]. All blind deconvolution algorithms require some partial knowledge about the input or imaging process. If the blind deconvolution algorithm considered is iterative and depends on many unknowns, it is in some cases difficult to appreciate any advantages it provides compared to non-blind iterative algorithms, whereby the PSF can be estimated empirically. One such example would be ground-based telescope imaging, whereby atmospheric turbulence plays a major role in the blurring function that is approximately Gaussian-shaped. In the quest, here, for a deconvolution algorithm, Solar System imaging has been used as a test bed for a blind deconvolution algorithm that is non-iterative.

Despite the number of unknowns in the blind algorithm, its results are comparable to many traditional algorithms. The advantage of getting a final result with a single iteration allows for a much more productive estimation of the blurring function. All frames in the sequence are used to restore the image since the low quality frames (e.g. the very blurred ones) would possibly degrade the fused result. A subset of images are carefully selected using three factors: sharpness, intensity similarity and detected ROI size. This operates under the assumption that most frames in the sequence contain fairly similar areas. Frames with significantly different content to others are likely to be greatly distorted.

CONCLUSION

A new method for mitigating atmospheric distortion in long-range surveillance imaging. Significant improvements in image quality are achieved using region-based fusion in the DT-CWT domain. This is combined with a new alignment method and cost function for frame selection to pre-process the distorted sequence. The process is completed with local contrast enhancement to reduce haze interference. CLEAR offers class-leading performance for off-line extraction of enhanced static imagery and has the potential to achieve high performance for on-line mitigation for full motion video—this is topic of ongoing research. a simple yet efficient algorithm for restoration of signals using a non-iterative blind deconvolution approach has been presented. It works for many image restoration cases whereby the blurring function is smooth and slowly varying. Many astronomical imaging cases suffer from this kind of degradation. The algorithm is further improved by adding the MTF of atmospheric turbulence into the formula making it optimized for a wide range of astronomical applications. The non-iterative nature of the algorithm and its computational simplicity enable convenient workflow to estimate various unknowns in a very short period of time.

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