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ANALYSIS ON BLUR IMAGE USING BLIND DECONVOLUTION TECHNIQUES

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ABSTRACT

Images are widely used in almost all technical areas for monitoring, detection newline medical diagnosis and so on. As the handheld camera or digital camera can notnewline capture images instantly, there is possibility of relative motion between the camera newline and scene being captured during exposure time causes unavoidable blurring effect in newlinecaptured images. Due to relative motion important information in the observed newline image is smeared and some of high frequency information is lost. Nowadays, trend newline is to use light weight digital camera and smart phone to capture images, but the newline resultant images from these devices are unevietably motion blurred as it is difficult hold these device steadily for long time. These blurred images are useless for further high quality image processing task. The Blind Image deconvolution/Deblurring (BID) newlineaims to recover sharp image from the corrosponding blurred image. It is long lasting newlineinverse problem, but still an imperative issue for research community to efficiently newlineand reliably restore the original image from available single blurred image. In real newlineworld scenario, motion deblurring is extremely essential for unique events such as, newlinesurveillance, astronomy, journalism, medical imaging, and consumer photography. newlinenewlineImage degradations mostly occur due to motion blur, out of focus blur or newlineatmospheric turbulence blur. In this thesis attempt has been made to remove newlineuniform motion blur effect from captured blurred photograph. Observed image is newlineusually represented by convolved mixture of original image and degradation newlinefunction. Therefore, motion deblurring task is composed of two part, first is to find newlineout the degradation function and secondly deconvolve the observed image using the newlinedegradation function to perform inverse operation so as to get back original image. NewlineIn Blind Deblurring problem degradation function is unknown and it is challenging to newlinefind out how the degradation has been occurred with little or no prior information newlineabout the image or the blurring process

1. INTRODUCTION

In electrical engineering and applied mathematics, **blinddeconvolution** is deconvolution without explicit knowledge of the impulse response function used in the convolution. This is usually achieved by making appropriate assumptions of the input to estimate the impulse response by analyzing the output. Blind deconvolution is not solvable without making assumptions on input and impulse response. Most of the algorithms to solve this problem are based on assumption that both input and impulse response live in respective known subspaces. However, blind deconvolution remains a very challenging non-convex optimization problem even with this assumption.

1.1 In image processing

In image processing, blind deconvolution is a deconvolution technique that permits recovery of the target scene from a single or set of "blurred" images in the presence of a poorly determined or unknown point spread function (PSF).[2]Regular linear and non-linear deconvolution techniques utilize a known PSF. For blind deconvolution, the PSF is estimated from the image or image set, allowing the deconvolution to be performed. Researchers have been studying blind deconvolution methods for several decades, and have approached the problem from different directions.

Most of the work on blind deconvolution started in early 1970s. Blind deconvolution is used in astronomical imaging and medical imaging.

Blind deconvolution can be performed iteratively, whereby each iteration improves the estimation of the PSF and the scene, or non-iteratively, where one application of the algorithm, based on exterior information, extracts the PSF. Iterative methods include maximum a posteriori estimation and expectation-maximization algorithms. A good estimate of the PSF is helpful for quicker convergence but not necessary.

Examples of non-iterative techniques include SeDDaRA,[3] the cepstrum transform and APEX. The cepstrum transform and APEX methods assume that the PSF has a specific shape, and one must estimate the width of the shape. For SeDDaRA, the information about the scene is provided in the form of a reference image. The algorithm estimates the PSF by comparing the spatial frequency information in the blurred image to that of the target image.

Limitation of Blind deconvolution is that both input image and blur kernel must live in fixed subspace. That means input image, represented by **w,** has to be written as **w=Bh,** where **B** is random matrix of size L by K (K<L) and **h** is of size K by 1, whereas blur kernel, if represented by **x,** has to be written as **x=Cm,** where C is random matrix of size L by N **(N<L)** and **m** is of size N by 1.Observed image, if represented by **y**, given by **y=w*x,** can only be reconstructed if L >=K +N.

1.2 In signal processing

Seismic data

In the case of deconvolution of seismic data, the original unknown signal is made of spikes hence is possibleto characterize with sparsity constraints[4] or regularization s such as l_1 **norm**/l_2 **norm** norm ratios,[5]suggested by W. C. Gray in 1978.[6]

Audio deconvolution

Audio deconvolution (often referred to as *dereverberation*) is

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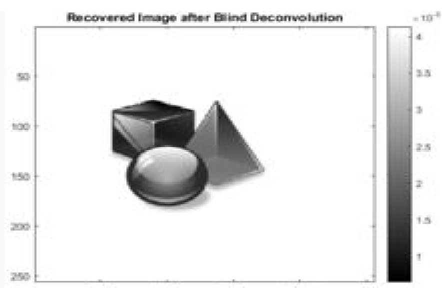
a reverberation reduction in audio mixtures. It is part of audio processing of recordings in ill-posed cases such as the cocktail party effect. One possibility is to use ICA.[7]

In general

Suppose we have a signal transmitted through a channel. The channel can usually be modeled as a linear shift-invariant system, so the receptor receives a convolution of the original signal with the impulse response of the channel. If we want to reverse the effect of the channel, to obtain the original signal, we must process the received signal by a second linear system, inverting the response of the channel. This system is called an equalizer.



Recovered image after applying algorithm of blind deconvolution. This algorithm basically solves optimization problem using nuclear norm minimization. L=65536, K=65 and N=44838,

If we are given the original signal, we can use a supervising technique, such as finding a Wiener filter, but without it, we can still explore what we do know about it to attempt its recovery. For example, we can filter the received signal to obtain the desired spectral power density. This is what happens, for example, when the original signal is known to have no auto correlation, and we "whiten" the received signal.

Whitening usually leaves some phase distortion in the results. Most blind deconvolution techniques use higher-order statistics of the signals, and permit the correction of such phase distortions. We can optimize the equalizer to obtain a signal with a PSF approximating what we know about the original PSF.

Original Image

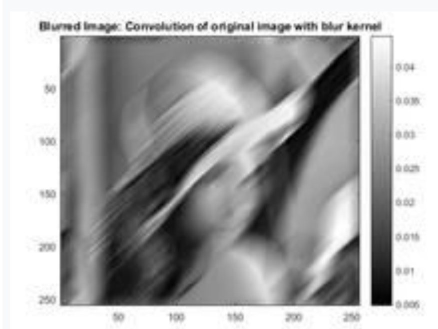


Fig.1: Blurred Image: obtained after the convolution of original image with blur kernel. Original image lies in fixed subspace of wavelet transform and blur lies in random subspace. L=65536, K=200, N=65400

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Fig.2: Recovered Image. recovered image is very different from original image, because essential condition for the algorithm of blind deconvolution using nuclear norm minimization is violated. L=L=65536, K=200, N=65400

High-order statistics

Blind deconvolution algorithms often make use of high-order statistics, with moments higher than two. This can be implicit or explicit.

Images are widely used in many kinds of applications such as everyday photography, monitoring, medical imaging, astronomy, microscopy, and remote sensing. Digital images are composed of picture elements or pixels that are organized in a grid. Each pixel contains an intensity value which determines the tone at a specific point. Unfortunately, all captured images end up more or less blurry. The motion of objects or the vibration of the sensor (camera) when pressing the shutter causes the image to be blurred. There are many factors that cause the blurring or degradationof the digital image, such as movement during the capture process, using long exposure times, using wide angle lens, etc.[2]. However, there are two main causes for motion blur: (i) the image is blurred by the camera vibration which causes all pixels in the image to be affected, and (ii) the image is blurred by object motion which causes a specific region to be blurred. Image blur usually devastate the images, and practically it is hard to avoid it because there is a lot of interference in the environment. Image deblurring is the process of applying and solving mathematical models to recover the original (sharp) image.

2. LITERATURE REVIEW

In 2000, Filipsroubek has proposed subspace based new multichannel blind deconvolution method developed for astronomical images. It was not iterative. It was computationally more efficient.In2003,FilipSroubek and Jan Flusser have proposed multichannel blind iterative image restoration, which is the edge preserving dancing technique. This is one step subspace based method. The conceptual and numerical problems of the single channel framework overcome by multichannel blind iterative image restoration. This method has some shortcomings which are the influence of misregistation and overestimated blur order.

Image blind deconvolution is solving the direct inversion of the illposed problem represented by linear restoration techniques which magnifies the accidental errors giving unacceptable results. To overcome this fact recognizes the image restoration problem should be treated by the methods of statistical estimation theory or regularization principles. The blind deconvolution approach used some methods for estimation of the regularization parameters which improve the result of image restoration. These methods are ARMA, GCV, ML, EM and NAS-RIF.

In 1997, Mitsuhiko Meguro has proposed new adaptive filter which is learning type of mean and median hybrid (LMMH) filters. This filter is a combination of FIR filtering and order statistics (OS) filtering for removing all types of distributed noise. This is an extension of wiener filter. The result of this filter is superior to wiener filter. In 2009, Yingying Kong has proposed new method of restoration and segmentation of SAR image. The adaptive filtering such as the median filter, Lee, and Gamma Map filter algorithms are used to compare with new MRF segmentation for reducing speckle noise from SAR images. In 2004, Fang Qiu has found that the local adaptive median filter outperformed others in achieving the best balance between speckle suppression and image detail preservation.

De and Masilamani presented a new method concerned the NR-IQA (No-reference Image Quality assessment). In this paper the standard deviation of Gaussian filter kernel is used for different images. This concept is used for deblurring the images. When there is blur increases in image the frequency component is decreases. So it is an image quality measure for the image. Image Quality measure is obtained after center Fourier transform for detecting sharpness in an image.

Saleh Al-amri, Kalyankar and Khamitkar S.D.]studied the method of Restored Gaussian Blurred Images when there is no information of PSF is given. In this paper different type of deblurring methods are compared and different experiments are done on different type of techniques, such as Wiener Filter, Lucy-Richardson Algorithm Method, Blind Deconvolution Algorithm Method, Regularized Filter Deblurring Method etc

Gavilan, R. Arahal and Ierardi presented their work on roll angle estimation. The estimation of plane angles is used to remove the blur in an image. Gradient algorithm is also used in this technique. These are basically vision enhanced methods for the aerial images. It is related to the automatic landing methods.

3. DEBLURRING TECHNIQUES

Deblurring is the process of removing blurring artifacts from images [input image say B which is blurred image which generally happens due to camera shake or some other phenomenon]. Now we want to recover Sharp Image S from blurred image which is B. Mathematically we represent B = S*K where B is blurred input image, we need to find out both sharp image S and K which is blur kernel and * is called convolution. We say that S is convolved with K to generate blurred image B, where K is the blur caused by defocus aberration, motion blur, gaussian blur or any kind of blur. So our goal is now to recover S which is Sharp image and also K and the process is known as Deblurring and some people called it Unblur too but Deblur is the correct technical word.

The blur K is typically modeled as point spread function and is convolved with a hypothetical sharp image S to get blurred Image B, where both the sharp image S (which is to be recovered) and the point spread function K are unknown. This is an example of an inverse problem. In almost all cases, there is insufficient information in the blurred image to uniquely determine a

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plausible original image, making it an ill-posed problem. In addition the blurred image contains additional noise which complicates the task of determining the original image. This is generally solved by the use of a regularization term to attempt to eliminate implausible solutions. This problem is analogous to echo removal in the signal processing domain. Nevertheless, when coherent beam is used for imaging, the point spread function can be modeled mathematically.[1] By proper deconvolution of the point spread function K and the blurred image B, the blurred image B can be deblurred (unblur) and the sharp image S can be recovered.

A. Blind Deconvolution Technique:

There are two types of deconvolution methods. They are projection based blind deconvolution and maximum likelihood restoration. In the first method it simultaneously restores true image and point spread function. This begins by making initial estimates of the true image and PSF. The technique is cylindrical in nature. Firstly we will find the PSF estimate and it is followed by image estimate. This cyclic process is repeated until a predefined convergence criterion is met. The advantage of this method is that it appears robust to inaccuracies of support size and also this method is insensitive to noise. The problem here is that it is not unique and this method can have errors associated with local minima. In the second approach the maximum likelihood estimate of parameters like PSF and covariance matrices. As the PSF estimate is not unique other assumptions like size, symmetry etc. of the PSF can be taken into account. The main advantage is that it has got low computational complexity and also helps to obtain blur, noise and power spectra of the true image. The drawback of this approach is that algorithm being converging to local minima of the estimated cost function.

B. Debluring with Blurred/Noisy Image Pairs:

In this method the image is deblurred with the help of noisy image. As a first step both the images the blurred and noisy image are used to find an accurate blur kernel. It is often very difficult to get blur kernel from one image. Following that a residual deconvolution is done and this will reduce artifacts that appear as spurious signals which are common in image deconvolution. As the third and final step the remaining artifacts which are present in the non-sharp images are suppressed by gain controlled deconvolution process. The main advantage of this approach is that it takes both the blurred and noisy image and as a result produces high quality reconstructed image. With these two images an iterative algorithm has been formulated which will estimate a good initial kernel and reduce deconvolution artifacts. There is no special hardware is required. There is also disadvantage with this approach like there is a spatial point spread function that is invariant.

C. Debluring with Motion Density Function:

In this method image debluring is done with the help of motion density function. A unified model of camera shake blur and a framework has been used to recover the

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camera motion and latent image from a single blurred image. The camera motion is express as a Motion Density Function (MDF) which records the fraction of time spent in each discretized portion of the space of all possible camera poses. Spatially varying blur kernels are derived directly from the MDF. One limitation of this method is that it depends on imperfect spatially invariant debluring estimates for initialization.

D. Debluring with Handling Outliers:

In this method various types of outliers such as pixels saturation and non-Gaussian noise are analysed and then a deconvolution method has been proposed which contains an explicit component for outlier modeling. Image pixels are classified into two categories: Inlier pixels and Outlier pixels. After that an Expectation Maximization method is employed to iteratively refine the outlier classification and the latent image.

E. Debluring by ADSD-AR:

In this approach ASDS (Adaptive Sparse Domain Selection) scheme is introduced, which learns a series of compact sub-dictionaries and assigns adaptively each local patch a sub-dictionary as the sparse domain. With ASDS, a weighted l1-norm sparse representation model will be proposed for IR tasks. Further two adaptive regularization terms has been introduced into the sparse representation framework. First, a set of autoregressive (AR) models are learned from the dataset of example image patches. The best fitted AR models to a given patch are adaptively selected to regularize the image local structures. Second, the image nonlocal self-similarity is introduced as another regularization term.

4. PROPOSED HTBMC PSF ESTIMATION ALGORITHM

The proposed Hough Transform of Binarized Modified Cepstrum (HTBMC)PSF estimation algorithm works with two assumptions. Firstly, Degradation present isdue to motion blur. Secondly, Motion blur considered is the global translation typewith no rotation. This section describes algorithms to determine motion blurparameters for uniform motion blur with noise and without noise. The block diagramis shown in Figure .3

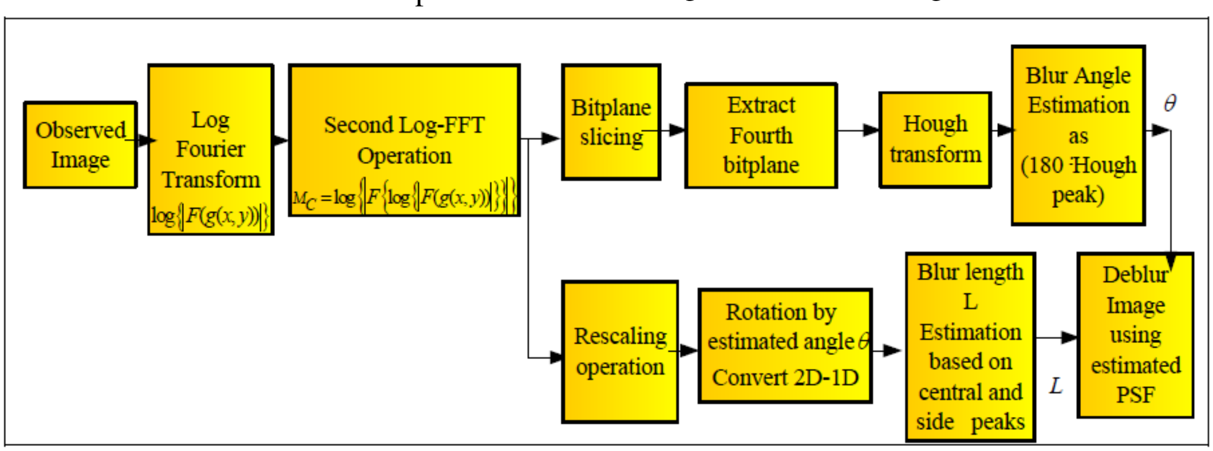

Figure .3: HTBMC based uniform motion blur PSF parameter estimation

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2581-4575
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Blur Direction Identification

In the proposed method central lobe of *Sinc*pattern is used for the blur angleestimation. To obtain thin and clear line in motion blur direction, dual log-FFToperation is used. It will increase angle estimation accuracy, resulting from thickcentral pattern. Still to create traces binarization is done with bitplane slicing. Out ofeight bit planes it is observed that fourth bitplane has perfect sharp line in thedirection of the blur. Hough transform is found on the fourth binary plane of Duallog-FFT operated image.The Hough transform method can be used for finding straight lines in an imagebecause lines can be easily detected as points in parameter space. One useful propertyof the Hough transform is that the pixel, which is on the line need not all, becontiguous. This can be very useful when trying to detect lines with short breaks inthem due to noise. A point in (x, y) space is represented by a curve in (ρ,θ) spacerather than a straight line where ρ is the distance between the origin and the line and θis line orientation as shown in Figure 4. Each image point (xi, yi) vote in (ρ,θ) spacefor line detection. The votes are summed in accumulator and picking largest value inaccumulator subtracted from 180 detects line corresponding motion blur direction inour proposed algorithm [2]

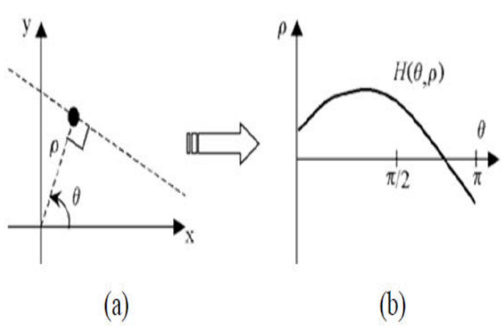

Figure .4: A spatial point on line represented in Hough transform (a) x-y space (b) θ- ρspacefor line detection

The steps for the Motion Blur Direction estimation are as follows:

- Compute log Fourier transform of motion blurred image $g(x, y)$ which is theconvolution of sharp image with blur kernel. In Fourier domain$G(u,v)$ $\rho H(u,v)F(u,v)$ and its log operation represent original image andblur components with additive combination (Figure .5.c).
- Repeat *Log* ρ*FFT* operation on resultant image which convert thick centrallobe of spectrum in to narrow strip and strengthen spectral zeros (Figure .5.d)
- Apply bitplane slicing on dual *Log* ρ*FFT* operated image and extract Fourthbitplane to find out the traces in direction of motion blur (Figure .5.e). Bitplane selection procedure is explained
- Hough transform is used for finding edge parameters based on peak value inthe accumulator array (Figure .5.f).
- Motion blur angle is identified as 180- the peak in Hough Transform. Blurangle values measured w.r.t. horizontal axis in anticlockwise direction.

Blur Length Estimation

Blur length estimation accuracy rest on the accuracy of estimated blur angle.Once the blur angle is accurately found, blur length estimation can be done. Blurlength estimation procedure is described below:

- Due to second FFT operation zero crossing will be converted into largenegative peaks known as cepstrum. Absolute values of these negative peaksare converted into positive peak represented with bright spots (Figure .5.d).

2581-4575
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- Rescale the dual *Log* **ρ** *FFT* operated image with threshold 0 .6. This willhelp in finding first zero crossing near to central lobe. Other zeros and noisewill be removed from the resultant image (Figure .5.g).
- Rotate the Rescaled resultant image by negative values of estimated angle.This will make the line traces horizontal.
- Convert the 2-D matrix of rotated rescaled image to 1-D by taking theaverages of columns. It will reflect the periodic zeros near to the central lobeclearly. It will show a peak in center corresponding to central lobe andhighlight the first zero crossing point after the central lobe on both the sides.The distance between the central peak and first larger peak on either side afterfirst zero crossings is nothing but the estimated blur length in pixels (Figure 5.h).Deblurring of the test image is done by this estimated PSF kernel. Construct PSF withestimated blur length and blur angle. Use the PSF in R-L based image restoration.Restored image is shown in (Figure.5.i).

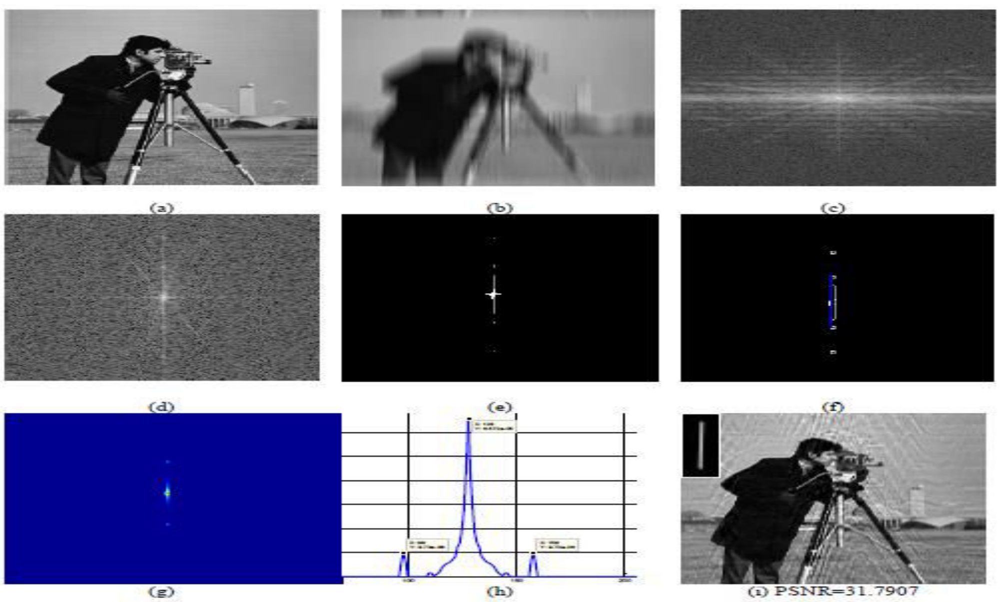

Figure 5: Results of proposed algorithm for uniform blur without noise (a) Originalcameraman (b) Blurred image with $L = 30pixels$ and $\theta = 90\ \rho$(c) log-FFT spectrum of motionblurred image (d) Modified cepstrum domain (e) Thin line segment extracted from fourthbitplane of modified cepstrum (f) Blur angle estimation using HT on line segment $\theta\hat{} = 89\ \rho$ (g)Grayscale transformation of modified cepstrum (h) Twin peak representation and blur lengthestimation $\hat{}L = 30pixels$ (i) Restored image with estimated PSF.

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CONCLUSION

Proposed HTBMC algorithm shows limited performance at specific angles and error increases under noisy conditions where it affects parallel lines in the spectrum. This performance may be due to image frequency components that are mixed with blur clues and causes problem in motion blur parameter identification. Classical restoration step after PSF estimation introduces ringing kind of artifacts that should be corrected for high quality. This thesis aimed to solve long lasting problem of motion blur removal from the captured photographs. Motion blur is most likely degradation that can happen during the imaging process due to relative motion between object and camera during exposure time. The main challenge is to find out correct blur-image pair from many such pairs that result in to same observed image without any prior knowledge about degradation or true image. It is more difficult to analyse the problem and find out the solution from single blurred image. This research work investigated the problem of blind image motion deblurring under spatially invariant conditions. deblurring.

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