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PHASE CONGRUENCY BASED DENOISING OF HISTORICAL DOCUMENT IMAGES

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Abstract

When Fourier component of image are maximally in phase then image features like edges, lines and match bands are present at that point. For detecting edges of image phase based method is more suitable than gradient based method because the phase is dimensionless quantity. Change in phase will not change the brightness or contrast of image. This provides a threshold value which can be applied over an image and binarized image is obtained. Here phase congruency features are calculated using wavelets. This paper provides the information about use of non-orthogonal, complex valued, log-Gabor wavelets, rather than the more usual orthogonal or bi-orthogonal wavelets. Thresholding of wavelet responses in the complex domain allows one to ensure that perceptually important phase information in the image is not corrupted. It is also shown how appropriate threshold values can be determined automatically from t1he statistics of the wavelet responses to the image

Keywords:Image Denoising, Phase-derived Features, Log Gabor wavelet, Binarization.

1. Introduction:

In Denoising of images is typically done with the following process: The image is transformed into some domain where the noise component is more easily identified, a thresholding operation is then applied to remove the noise, and finally the transformation is inverted to reconstruct a (hopefully) noise-free image.

The wavelet transform has proved to be very successful in making signal and noise components of the signal distinct. As wavelets have compact support the wavelet coefficients resulting from the signal are localized, whereas the coefficients resulting from noise in the signal are distributed. Thus the energy from the signal is directed into a limited number of coefficients which 'stand out' from the noise. Wavelet shrinkage denoising then consists of identifying the magnitude of wavelet coefficients one can expect from the noise (the threshold), and then shrinking the magnitudes of all the coefficients by this amount. What remains of the coefficients should be valid signal data, and the transform can then be inverted to reconstruct an estimate of the signal [4, 3, 1].

Wavelet denoising has concentrated on the use of orthogonal or bi-orthogonal wavelets because of their reconstructive qualities. However, no particular wavelet has been identified as being the 'best' for denoising. It is generally agreed that wavelets having a linear-phase, or near linear phase, response are desirable, and this has led to the use of the 'symlet' series of wavelets and bi-orthogonal wavelets. A problem with wavelet shrinkage denoising is that the discrete wavelet transform is not translation invariant. If the signal is displaced by one data point the wavelet coefficients do not simply move by the same amount. They are completely different because there is no redundancy in the wavelet representation. Thus, the shape of the reconstructed signal after wavelet shrinkage and transform inversion will depend on the translation of the signal - clearly this is not very satisfactory. To overcome this translation invariant de- noising has been devised [1]. This involves averaging the wavelet shrinkage denoising result over all possible translations of the signal. This produces very pleasing results and overcomes pseudo-Gibbs phenomena that are often seen in the basic wavelet shrinkage denoising scheme.

The criteria for quality of the reconstructed noise-free image has generally been the RMS error - though Donoho suggests a side condition that the reconstructed (denoised) signal should be, with high probability, as least as smooth as the original (noise free) signal.While the use of the RMS error in reconstructing 1D signals may be reasonable, the use of the RMS measure for image comparison has been criticized[2, 10]. Almost without exception images exist solely for the benefit of the human visual system. Therefore any metric that is used for evaluating the quality of image reconstruction must have relevance to our visual perception system. The RMS error certainly does not necessarily give a good guide to the perceptual quality of an image reconstruction. For example, displacing an image a small amount, or offsetting grey levels by involved in extending this theory to the images. It is shown that for good localization it is important to consider the spread of frequencies present at a point of phase congruency. The issue of analysis at different scales is then considered and it is argued that high pass filtering should be used to obtain image information at different scales instead of the more usually applied low pass filtering. Finally some results and the conclusion are presented. An appendix containing implementation details is also included

2 Related Work:

In this section, some binarization methods are briefly described. Sauvola et al. [3] propose an adaptive binarization method based in which image is divided in to sub components like text, background and picture. Two algorithms are used to calculate pixel threshold. In [4] Gatos et al. uses low pass filter and estimate surface foreground and background in degraded image binarization. In [1] Su et al proposed a robus binarization method, which is based on adaptive image contrast. Constructed adaptive contrast map of degraded document is binarized and combined with canny edge map to find text stoke edge pixels. Then local threshold is estimated for segmentation of document text using intensities of detected text strokes.

In [6] proposed method mainly for handwritten documents. In which background estimation and global binarization is performed with normalized image. In binarization stroke width and contrast are estimated and very small components are removed. Then local adaptive binarization is performed and combined. In [2] adaptive and parameterless Otsu’s method is generated. Grid based modeling and background map estimation is combined to get adaptive behavior. By estimating parameters like average stoke width and average line height parameterless behavior is achieved. In [5] proposed method uses maximum likely hood classification and The proposed approach is based on maximum likelihood (ML) classification, priori information and the spatial relationship of image domain. It uses soft decision based on a probabilistic model.to recover main text it contain dark part of image including weak strokes and low intensity. Text and background features are estimated using grid-based modeling and inpainting techniques then ML is applied.

In [8] Su et al. proposed a self-training learning framework for document image binarization. This method first divide image into three parts namely foregrounds pixels, background pixels and uncertain pixels using a trained classifier. And uncertain pixels are classified. In [7] lu et al. proposed binarization method using local image maximum and minimum. Local maximum and minimum is more tolerant to different types of document degradation than image gradient. Kovasi [10] proposed a method to obtain phase preserving denoising image. It uses non-orthogonal, complex valued, log-Gabor wavelets because in complex domain after thresholding of wavelet responses the phase information in the image is not corrupted. It also determine threshold value automatically from the statistics of the wavelet responses to the image.

3 Methodology:

1. Denoising of image:

An image denoising method proposed by Kovesi is used in this paper, which is based on the assumption that phase data is the most essential component of images. This method also attempts to preserve the perceptually vital phase data in the signal. It uses non-orthogonal, complex valued log-Gabor wavelets, which separate the neighborhood phase and amplitude data at every point in the image. The denoising process consists of deciding a noise threshold at every scale and shrinking the magnitudes of the filter response vector properly, while leaving the phase unaltered. Programmed estimation of these noise thresholds, using the statistics of the smallest filter scale response, is the most essential piece of denoising. These statistics are used to estimate the distribution of the noise amplitude, because they give the strongest noise response. At that point, the noise amplitude distribution of other filter scales can be estimated relatively.

To have the capacity to preserve the phase information in an image we need to first concentrate the nearby phase and amplitude data at every point in the image. This should be possible by applying (a discrete execution of) the continuous wavelet transform and using wavelets that are in symmetric/anti-symmetric pairs. Here we take after the methodology of Morlet, that is, using wavelets based on complex valued Gabor functions - sine and cosine waves, each tweaked by a Gaussian. Using two filters in quadrature enables one to figure the amplitude and phase of the signal for a specific scale/recurrence at a given spatial area.

Nonetheless, as opposed to using Gabor filters we like to use log Gabor functions as suggested by Field ; these are filters having a Gaussian transfer capacity when seen on the logarithmic recurrence scale. Log Gabor filters permit subjectively vast bandwidth filters to be constructed while still keeping up a zero DC part in the even-symmetric filter. A zero DC value can't be kept up in Gabor functions for bandwidths more than 1 octave. It is of interest to note that the spatial degree of log Gabor filters appears to be minimized when they are constructed with a bandwidth of roughly two octaves. This would give off an impression of being ideal for denoising as this will minimize the spatial spread of wavelet response to signal features, and thus think as much signal energy as possible into a set number of coefficients.

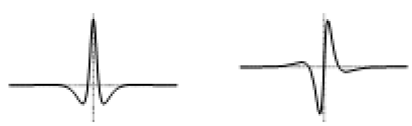

Fig1: Even and odd log Gabor wavelets.

Analysis of a signal is finished by convolving the signal with each of the quadrature pairs of wavelets. In the event that we let $f(x)$ signify the signal and M_p^e and M_p^o mean the even-symmetric and odd-symmetric wavelets at a scale n we can think about the responses of every quadrature pair of filters as shaping a response vector,

$$[e_p(x), o_p(x)] = [f(x) * M_p^e, f(x) * M_p^o] \qquad (4.10)$$

The values $e_p(x)$ and $o_p(x)$ can be considered as real and imaginary parts of complex valued recurrence segment. The amplitude $A_p(x)$ of the transform at a given wavelet scale is given by

$$A_p(x) = \sqrt{e_p(x)^2 + o_p(x)^2} \qquad (4.11)$$

and the phase $\Phi_p(x)$ is given by

$$\Phi_p(x) = arctan2(o_p(x), e_p(x)) \qquad (4.12)$$

At every point x in a signal we will have a variety of these response vectors, one vector for every scale of filter

2. Determining the noise threshold:

The most urgent parameter in the denoising process is the threshold. While numerous procedures have been produced, none have demonstrated exceptionally palatable. Here we build up a programmed thresholding plan.

To start with we should take a gander at the normal reaction of the filters to an immaculate noise signal. On the off chance that the signal is simply Gaussian repetitive sound positions of the subsequent reaction vectors from a wavelet quadrature pair of filters at some scale will frame a 2D Gaussian distribution in the complex plane. What we are occupied with is the distribution of the extent of the reaction vectors. This will be a Rayleigh distribution where is the change of the 2D Gaussian distribution portraying the position of the channel reaction vectors.

$$R(x) = \frac{x}{\sigma_G^2} exp^{\frac{-X^2}{2\sigma_G^2}} \qquad (4)$$

The mean of the Rayleigh distribution is given by

$$\mu_R = \sigma_G \sqrt{\frac{\pi}{2}} \qquad (5)$$

and the variance is

$$\sigma_R^2 = \left(2 - \frac{\pi}{2}\right)\sigma_G^2 \qquad (6)$$

The point to note is that one and only parameter is required to depict the distribution; given one can decide, and the other way around. On the off chance that we can decide the noise reaction distribution at every channel scale we could then set the noise shrinkage threshold at every scale to be some number of standard deviations past the mean of the distribution

$$T = \mu_R + k\sigma_R \qquad (7)$$

where k is typically in the range 2 – 3.

In what capacity would we be able to decide the noise amplitude? The littlest scale filter has the biggest bandwidth, and thusly will give the most grounded noise response. Just at feature points will the response vary from the background noise

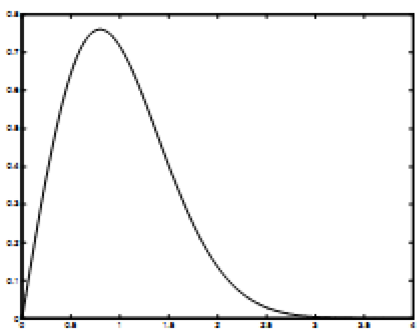

Fig2. Rayleigh distribution with a mean of one.

response, yet the districts where it will react to features will be little because of the little spatial degree of the filter. In this manner the littlest scale wavelet quadrature pair will invest the vast majority of their energy just responding to noise.

Accordingly, the distribution of the amplitude response from the littlest scale filter pair over the entire image will be principally the noise distribution, that is, a Rayleigh distribution with some tainting as an aftereffect of the response of the filters to feature points in the image.

We can get a strong estimate of the mean of the amplitude response of the littlest scale filter by means of the median response. The median of a Rayleigh distribution is the quality x such that

$$\frac{x}{\sigma_G^2} exp^{\frac{-x^2}{2\sigma_G^2}} = \frac{1}{2}$$

$$median = \sigma_G \sqrt{-2\log(1/2)}$$

Noting that the mean of the Rayleigh distribution is $\sigma_G \sqrt{\frac{\pi}{2}}$ we obtain the expected value of the amplitude response of the smallest scale filter (the estimate of the mean)

$$\mathrm{E}(A_N) = \frac{\sigma_G \sqrt{\pi/2}}{\sigma_G \sqrt{-2\log(1/2)}} \cdot median$$

$$= \frac{1}{2} \frac{\sqrt{-\pi}}{\sqrt{\log(1/2)}} \cdot median$$

Here N is the index of the smallest scale filter. Given that $\sigma_G = \frac{E(A_N)}{\sqrt{\pi/2}}$ then we can estimate μ_R and σ_R for the noise response for the smallest scale filter pair, and hence the shrinkage threshold. We can estimate the fitting shrinkage thresholds to use at the other filter scales in the event that we mention the accompanying objective fact: If it is accepted that the noise spectrum is uniform then the wavelets will accumulate energy from the noise as a component of their bandwidth which, thusly, is an element of their center frequency. For 1D signal the amplitude response will be proportional to the square root of the filter center frequency. In 2D images the amplitude response will be straightforwardly proportional to the filter center frequency.

Therefore having gotten an estimate of the noise amplitude distribution for the littlest scale Filter pair we can basically scale this properly to shape estimates of the noise amplitude distributions at all alternate scales. This methodology turns out to be exceptionally effective in permitting shrinkage thresholds to be set naturally from the measurements of the littlest scale filter response over the entire image.

5.2.2 AdOtsu method based on the estimated background:

We call the adaptive adaptations of Otsu's method the AdOtsu methods. In this area, another AdOtsu method giving prevalent execution is presented, which is based on the estimated background (EB). Along these lines, the method is parameterless like Otsu's method itself, and in this manner is less delicate to minor departure from the info record image.

In the proposed AdOtsu method, we dole out a threshold quality to every pixel on the image space. On the off chance that the pixel worth is not as much as that threshold, the pixel is viewed as a text pixel, else it is named a background pixel. The accompanying adaptive threshold worth is utilized for every pixel x :

$$T_{AdOtsu\,,u}(x) = \epsilon + \left(\underset{t}{argu\ max} \left(\frac{{\sigma_{bet}}^2(x)}{{\sigma_{tot}}^2(x)} \right) - \epsilon \right) \theta(\sigma(x) - 1k_{\sigma}\sigma_{EB}(x))$$

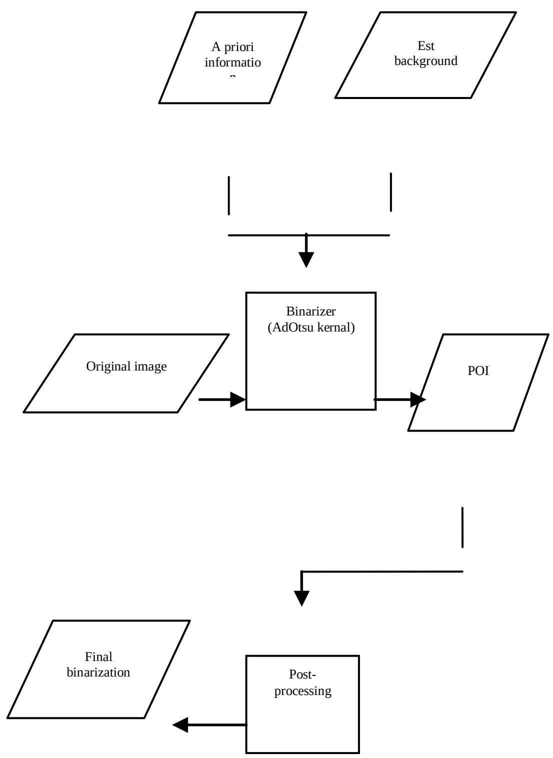

Fig 3: The proposed AdOtsu binarization method using the estimated background (EB) to locate the non-text regions

The first term in brackets is Otsu's threshold figured on a patch around x. The little esteem E is considered for numerical strength. The unit step function, indicated by θ, controls the conduct of the method based on the variance of the information image and the estimated background (EB). The standard deviations of u and u_{EB}, denoted as $\sigma(x)$ and $\sigma_{EB}(x)$ individually a recalculated on the same patch.

At long last, k_{σ} is a variable somewhere around 1 and 2 used to include a hysteresis conduct in the switch? In a nutshell, if the minor departure from the information image close x is not exactly an element of that of the EB, ϵ will be utilized as the threshold and x will be relegated to the background. Conversely, if $\sigma(x)$ is high, Otsu's method is utilized, yet on a neighborhood patch around x. Thusly, the method advantage from the upsides of Otsu's method, while in the meantime being totally adaptive. This is the fundamental favorable position of the proposed method contrasted with that in [1 0], which is confined by its high reliance on the worldwide threshold esteem. This can be seen from Table 3 in Experimental Results area, which demonstrates that the grid based Sauvola method performs better.

IV. Experimental Results

1. Subjective Evaluation:

In this section, different results after performing several operations on degraded image document are given.First we obtain denoised image of input image. Then normalize that denoised image by using linear transform. After that binarized images of original image and normalized denoised image are obtained by using AdOtsu method of binarization. Use canny edge operator to find edge map image and combine output of canny edge operator with binarized normalized denoised image.

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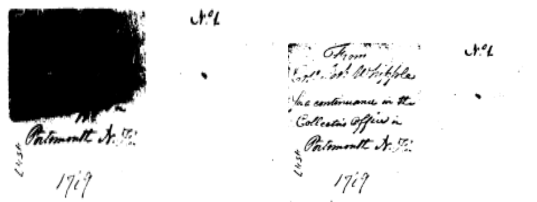
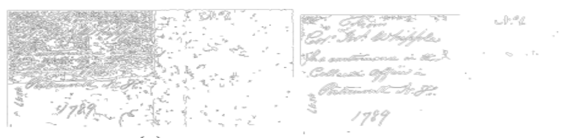
(a) (b)



(C) (d)



(e) s (f)

Fig 4. a)Denoised image. b) Normalized denoised image. c) Binarization of the original image using AdOtsu's method. d) Binarization of the normalized denoised image using AdOtsu's method. e) Edge image using the Canny operator. f) Combination of (d) and (e).

IV Conclusion:

We have presented a new denoising algorithm, based on the decomposition of a signal using complex valued wavelets. This algorithm preserves the perceptually important phase information in the signal. In conjunction with this a method has been devised to automatically determine the appropriate wavelet shrinkage thresholds from the statistics of the amplitude response of the smallest scale filter pair over the image. The automatic determination of thresholds overcomes a problem that has plagued wavelet denoising schemes in the past. The RMS measure is not always the most appropriate metric to use in the development of image processing algorithms. Indeed it could be argued that more time should be spent optimizing the choice of the optimization criteria in general. For images it would appear that the preservation of phase data is important, though of course, other factors must also be important. The denoising algorithm presented here denoised with phase preserved does not seek to do any optimization; it has merely been constructed so as to satisfy the constraint that phase should not be corrupted. Given that it satisfies this constraint, it should be possible to develop it further so that it does incorporate some optimization, say, the minimization of the distortion of the signal's amplitude spectrum. What should also be investigated is the possible relationship between this phase preserving algorithm and translation invariant denoising

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