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Binarization of Historical Document Images Using Phase Congruency

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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 a image and binarized image is obtained. Here phase congruency features are calculated using wavelets. The existing theory that has been developed for signals is extended to allow the calculation of phase congruency in 2D images. It is shown that for good localization it is important to consider the spread of frequencies present at a point of phase congruency. An effective method for identifying and compensating for the level of noise in an image is presented. Finally it is argued that high pass filtering should be used to obtain image information at different scales. With this approach the choice of scale only acts the relative signicance of features without degrading the localization

KEYWORDS: feature detection, phase-derived features, binarization**.**

I. INTRODUCTION

In searching for parameters to describe the significance of image features such as edge s we should be looking for dimensionless quantities in particular measures that are invariant with respect to image illumination and magnification. Such quantities would provide an absolute measure of the significance of feature points that could be applied universally to any image irrespective of image illumination and magnification.

Gradient based edge detection methods such as those developed by Sobel Pringle Marr and Hildreth Canny and others are sensitive to image illumination variations Intensity gradient has units of lumens/radian pixel co ordinate s represent viewing direction and hence have angular units. Intensity gradients in images depend on many factors including illumination blurring and magnication. For example doubling the size of an image while leaving its intensity values unchanged will halve all the gradients in the image. Any gradient based edge detection process will need to use a threshold.

This paper describes a new way of calculating phase congruency using Gabor wavelets and is organized as follows. The theory behind the calculation of phase congruency in one dimensional signals is introduced. It is then shown how phase congruency can be calculated from Gabor wavelets geometrically scaled spatial filters in quadrature. The paper then moves on to consider the effect of noise in the calculation of phase congruency and develops an effective method for identifying and compensating for these effects. This is followed by a section covering the issues 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

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II. 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.

III. BINARIZATION USING PHASE CONGRUENCY

1. Denoising of image:

To be able to preserve the phase data in an image we have to first extract the local phase and amplitude information at each point in the image. This can be done by applying (a discrete implementation of) the continuous wavelet transform and using wavelets that are in symmetric/anti-symmetric pairs. Here we follow the approach of Morlet, that is, using wavelets based on complex valued Gabor functions - sine and cosine waves, each modulated by a Gaussian. Using two filters in quadrature enables one to calculate the amplitude and phase of the signal for a particular scale/frequency at a given spatial location.

However, rather than using Gabor filters we prefer to use log Gabor functions as suggested by Field; these are filters having a Gaussian transfer function when viewed on the logarithmic frequency scale. Log Gabor filters allow arbitrarily large bandwidth filters to be constructed while still maintaining a zero DC component in the even-symmetric filters. A zero DC value cannot be maintained in Gabor functions for bandwidths over 1 octave. It is of interest to note that the spatial extent of log Gabor filters appears to be minimized when they are constructed with a bandwidth of approximately two octaves. This would appear to be optimal for denoising as this will minimize the spatial spread of wavelet response to signal features, and hence concentrate as much signal energy as possible into a limited number of coefficients.

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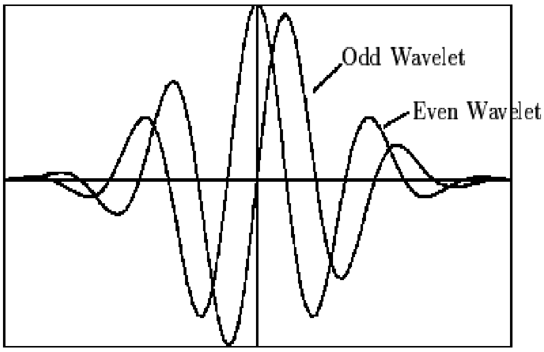

Figure1. Even and odd log Gabor wavelets, each having a bandwidth of two octaves.

Analysis of a signal is done by convolving the signal with each of the quadrature pairs of wavelets. If we let I denote the signal and Me and Mo denote the even-symmetric and odd-symmetric wavelets at a scale n we can think of the responses of each quadrature pair of filters as forming a response vector,

$$[e_p(x), o_p(x)] = [f(x) * M_p^e, f(x) * M_p^o] \quad (1)$$

The values en(x) and on(x) can be thought of as real and imaginary parts of complex valued frequency component. The amplitude of the transform at a given wavelet scale is given by

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

and the phase is given by

$$\Phi_p(x) = arctan2(o_p(x), e_p(x)) \quad (3)$$

At each point x in a signal we will have an array of these response vectors, one vector for each scale of filter. These response vectors form the basis of our localized representation of the signal

The most crucial parameter in the denoising process is the threshold. While many techniques have been developed, none have proved very satisfactory. Here we develop an automatic thresholding scheme.

First we must look at the expected response of the filters to a pure noise signal. If the signal is purely Gaussian white noise the positions of the resulting response vectors from a wavelet quadrature pair of filters at some scale will form a 2D Gaussian distribution in the complex plane. What we are interested in is the distribution of the magnitude of the response vectors. This will be a Rayleigh distribution where $\sigma_G^2$is the variance of the 2D Gaussian distribution describing the position of the filter response vectors.

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

The mean of the Rayleigh distribution is given by

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

and the variance is

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

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The point to note is that only one parameter is required to describe the distribution; given μ_R one can determine, σ_R and vice-versa. If we can determine the noise response distribution at each filter scale we could then set the noise shrinkage threshold at each scale to be some number of standard deviations beyond the mean of the distribution

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

where k is typically in the range 2 – 3.

How can we determine the noise amplitude distribution? The smallest scale filter has the largest bandwidth, and as such will give the strongest noise response. Only at feature points will the response differ from the background noise.

2. Binarization using phase congruency feature map:

If we design our bank of wavelet filters so that the transfer function of each filter overlaps sufficiently with its neighbors in such a way that the sum of all the transfer functions forms a relatively uniform coverage of the spectrum we are in a position to reconstruct the decomposed signal over a band of frequencies up to a scale factor. If the transfer functions are scaled so that their sum is always one exact reconstruction will be achieved. Referring to Figure one can see that the sum of the spectra of the wavelets produces a relatively ideal band pass filter especially when viewed on the log frequency scale. Design of the wavelet bank ends up being a compromise between wishing to form a smooth sum of spectra and at the same time minimizing the number of filters used so as to minimize the computation requirements.

If we sum the results of convolving our signal with the bank of even wavelets we will reconstruct a band passed version of our signal amplified according to the scaling and overlap of the transfer functions of our filters. We can use this result for F(x) and H(x) can be constructed from the sum of the convolutions of the signal with the odd wavelets this is a signal covering the same bandwidth of the original signal and amplified in the same way as F(x) but shifted in phase by 90. Thus

$$PC(x) = \frac{E(X)}{\varepsilon+\sum_n A_n(x)} \quad (8)$$

Where $E(X) = \sqrt{F(x)^2 + H(x)^2}$

The fractional measure of spread *s(x)* is defined in eq (9) in which filter scale is denoted as N and amplitude of filter pair is denoted as $A_{max}(x)$.

$$s(x) = \frac{1}{N}\left(\frac{\sum_p A_p(x)}{A_{max}(x)}\right) \quad (9)$$

Phase congruency weighting mean function *W(x)* is defined in equation (6). Where cut of value of filter response spread is denoted as *c* and gain factor which controls sharpness of the cutoff is denoted as γ.

$$W(x) = \frac{1}{1+e^{\gamma(c-s(x))}} \quad (10)$$

$\Delta\Phi_p(x)$ This is a sensitive phase deviation function, is defined as follows in which $\emptyset_p(x)$ is mean phase angle.

$$\Delta\Phi_{pr}(x) = \cos\left(\emptyset_p(x) - \emptyset\hat{}(x)\right) - \left|\sin\left(\emptyset_p(x) - \emptyset\hat{}(x)\right)\right| \quad (11)$$

The one-dimensional phase congruency is indicated asPC_{1D} . Where $\lfloor A_p(x)\Delta\Phi_p(x)\rfloor$ is equal to zero when its value become negative otherwise original value is considered.

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$$PC_{1D}(x) = \frac{\sum_p W(x)\lfloor A_p(x)\Delta\Phi_p(x)\rfloor}{\sum_p A_p(x)} \qquad (12)$$

To overcome from noise sensitivity of $PC_{1D}(x)$ apply noise threshold to the equation (7).

$$PC_{1D}(x) = \frac{\sum_p W(x)[A_p(x)\Delta\Phi_p(x) - T]}{\sum_p A_p(x)} \qquad (13)$$

To calculate phase congruency in two dimensions consider both scale (p) and orientation (r).Then it is calculated according to equation (15).

$$PC_{2D,r}(x) = \frac{\sum_p W_r(x)[A_{pr}(x)\Delta\Phi_{pr}(x) - T_r]}{\sum_p A_{pr}(x)} \qquad (14)$$

Then phase deviation function is calculated using following equation:

$$\Delta\Phi_{pr}(x) = \cos(\emptyset_{pr}(x) - \emptyset_r\hat{}(x)) - |\sin(\emptyset_{pr}(x) - \emptyset_r\hat{}(x))| \qquad (15)$$

Function of the maximum moment of phase congruency covariance (*IM*) is to measure edge strength, which measures in a range [0 1]. Larger value indicates stronger edge strength.

$$I_M = \max_r PC_{2D,r}(x) \qquad (16)$$

By taking summation of all filter values with respect to both filter scale and orientation locally weighted mean phase angle I_L is calculated. Range of I_L is $-\pi/2$ to $\pi/2$. $-\pi/2$ indicates dark line and $-\pi/2$ indicates bright line of pixel.

$$I_L(x) = arctan[\sum_{p,r} e_{pr}(x), \sum_{p,r} o_{pr}(x)] \qquad (17)$$

IV. EXPERIMENTAL RESULTS

H-DIBCO’10 dataset is used to evaluate and compare result with other methods. A set of images with different type of degradation is present in these types of datasets. It gives good platform to evaluate proposed method and to allow a significant test of different algorithm.

Here evaluation is carried using two methods objective and subjective evaluation. In these types comparison of proposed method with other binarization methods is carried out on the basis of subjective and objective performance.

A. Subjective Evaluation

In this section, we compare outputs of the proposed method with different methods which places top ranks in contest. Our method uses phase congruency features and phase preserved denoised image to perform binarization.

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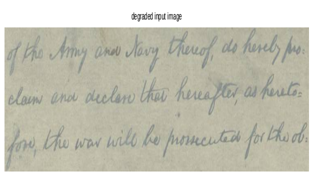

Fig 2.Input Image

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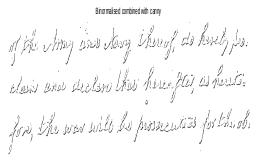

Fig 3.Combination of binarization of the normalized denoised image and canny edge image

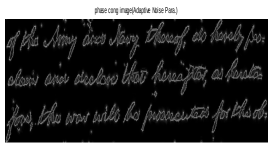

Fig 4.Phase congruency with adaptive noise parameter

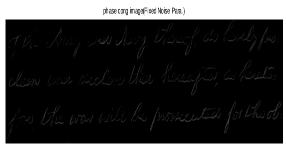

Fig 5.Phase congruency with fixed noise parameter

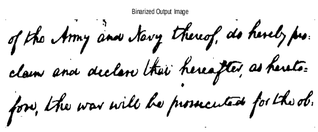

Fig 6.Output of binarization

V. CONCLUSION

The phase preserved feature maps are computed to build model for binarization of ancient documents. Three phase preserved feature maps are locally weighted mean phase angle, maximum moment for phase congruency covariance and a phase preserved denoised image. The output of preprocessing is rough binarized image. Then two phase congruency features are derived in main binarization. In post processing Gaussian and median filter is used to improve output of main binarization. These filters are used to remove noise, unwanted lines, and interfering patterns and it also helps to separate foreground and background pixels. The manual correction is deduced based on this tool which is involved in ground truth generation. The application of phase-derived features, the stable behaviour of document images, to other cultural heritage fields, can be maintained for long time. So, they are very useful to our future generation to follow the ancient culture and their traditions. And also our historical documents can be saved.

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