An Iterative Approach to Improved Local Phase Coherence Estimation

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Abstract

This paper introduces a novel iterative approach to estimating local phase coherence in situations characterized by low signal-to-noise ratios. Local phase coherence is used for a wide range of computer vision applications such as edge and corner detection and object description. An issue faced in extracting local phase coherence is the presence of image noise. While existing approaches to dealing with noise when estimating local phase coherence is effective for low noise situations, they are inadequate for situations contaminated by high levels of noise. In the proposed approach, the issue of high image noise is addressed by re-estimating both the local phase coherence and the underlying image content iteratively to improve local phase coherence estimates. This is performed using a feedback loop model, where the local phase coherence estimates are used to re-estimate the image content using a moment-adaptive bilateral estimation scheme and information from the re-estimated image content is used to re-estimate the local phase coherence. Experiment results show that the proposed approach can be used to provide improved local phase coherence estimates.

1 Introduction

Within the past few decades, wavelets have become one of the most widely-used tools in the field of computer vision. This wide-spread use of wavelets can be partly attributed to the fact that wavelets have been shown to provide a good basic model of the human vision system [1]. In the wavelet-based view of the human vision system, local frequency information such as amplitude and phase is extracted and processed by the human vision system to obtain perceptually significant information about the environment. Given how robust the human vision system is at extracting important features under various conditions such as scale changes, noise, and illumination variations, researchers in the field of computer vision are highly motivated to use wavelets for the purpose of feature extraction and representation.

In recent years, wavelet-based computer vision research has focused on the use of local phase characteristics. There are several advantages to using local phase characteristics for feature representation. Local phase provides important information about the structural characteristics of a scene [2, 3]. Furthermore, since only phase information is used, local phase characteristics are largely invariant to illumination and contrast conditions. One particularly effective local phase characteristic used for the purpose of feature representation is local phase coherence. The use of local phase coherence is motivated by the theory that local phase coherence corresponds to the perceptual significance of visual data. Physiological evidence has shown that the human vision system has respond strongly to visual data with high local phase coherence [1]. Motivated by the benefits of local phase and its biological ties to the human vision system, the concept of local phase coherence have been used in a wide variety of computer vision applications such as face recognition [5, 4], blur analysis [6], medical analysis [7, 8], and image registration [9].

One of the biggest challenges to extracting local phase coherence from an image for the purpose of feature representation is dealing with the presence of image noise. Extracting local phase coherence in situations characterized by high levels of noise can result in highly degraded features with little useful information pertaining to the structural characteristics of the scene. While local phase coherence estimation methods such as that proposed by Kovesi [10] account for image noise, these noise reduction mechanisms are only suitable for low noise situations. Therefore, a more robust approach to local phase coherence estimation that can handle situations with high noise levels is desired.

The main contribution of this paper is a novel iterative approach to improved local phase coherence estimation. The moments of local phase coherence are estimated and used to re-estimate the image content using a moment-

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adaptive bilateral estimation scheme. The estimated image content is then used to re-estimate the local phase coherence. This process is performed iteratively using a feedback loop model to refine the estimated local phase coherence. An overview of local phase coherence estimation is described in Section 2. The proposed approach is described in detail in Section 3. Experimental results are presented and discussed in Section 4. Finally, conclusions are drawn in Section 5.

2 Local Phase Coherence

Prior to describing the proposed approach, it is important to first provide an overview of how local phase coherence can be estimated from an image. One of the most widely-used local phase coherence estimation methods is that proposed by Kovesi [10], which has been found to provide good feature localization and robustness to low levels of noise. As such, this method will be the basis of the proposed local phase coherence estimation approach. Given an image I, the amplitude A and phase ϕ at a given point can be obtained using logarithmic Gabor wavelets. The local amplitude and phase for a given point $\underline{x}$ at wavelet scale n can be expressed as follows:

$$A_n(\underline{x}) = \sqrt{\left(I(\underline{x}) * F_n^e\right)^2 + \left(I(\underline{x}) * F_n^o\right)^2} \tag{1}$$

$$\phi_n(\underline{x}) = \tan^{-1}\left(\frac{(I(\underline{x}) * F_n^e)}{(I(\underline{x}) * F_n^o)}\right) \tag{2}$$

where F_n^e and F_n^o are the even-symmetric and odd-symmetric wavelets at scale n. The local phase coherence at point $\underline{x}$ and orientation θ can then be estimated using the following expression:

$$P(\underline{x},\theta) = \frac{\sum\limits_n W(\underline{x},\theta) \left\lfloor A_n(\underline{x},\theta)\, \Delta\Phi(\underline{x},\theta) - T \right\rfloor}{\sum\limits_n A_n(\underline{x},\theta) + \varepsilon} \tag{3}$$

$$\Delta\Phi(\underline{x},\theta) = \cos\left(\phi_n(\underline{x},\theta) - \bar{\phi}(\underline{x},\theta)\right) - \left|\sin\left(\phi_n(\underline{x},\theta) - \bar{\phi}(\underline{x},\theta)\right)\right| \tag{4}$$

where W represents the frequency spread weighting factor (coherence when frequency spread is high is weighted more than coherence when frequency spread is low), $\bar{\phi}$ represents the weighted mean phase, T represents the noise threshold and ε is a small constant used to avoid division by zero. When the wavelet components are maximally in phase, $\Delta\Phi$ goes to zero and P goes approximately to one (if the amplitudes are non-zero). For testing purposes, the parameters used to determine local phase coherence are the same as that used in [10].

As mentioned in Section 1, one of the biggest challenges in obtaining useful local phase coherence information from an image is in dealing with image noise. The aforementioned local phase coherence estimation approach attempts to reduce the effects of image noise by integrating a noise threshold into the estimation process. While this works in situations characterized by a low level of image noise, there are several problems when dealing with situations characterized by low signal-to-noise ratios. First, the noise threshold is set to a fixed value. As such, it is not suitable for handling situations characterized by different or varying noise levels. More importantly, while the noise threshold reduces the effect of noise on the local phase estimation process, it also prunes important local phase coherence information that share similar characteristics as the image noise. This is particularly problematic in situations characterized by high noise level since local phase characteristics are often difficult to distinguish from noise. An example of this can be seen in Fig. 1, where the local phase coherence is estimated for an image contaminated by a high level of noise. It can be seen that the estimated local phase coherence information provides very little information about the structural characteristics of the image content. As such, an estimation approach that, in conjunction with the existing noise threshold mechanism, can be used to obtained improved local phase coherence information is desired.

3 Proposed Approach

To improve the quality of the estimated local phase coherence in situations characterized by low signal-to-noise ratios, we propose an iterative approach that re-estimates the local phase coherence as well as the underlying image content using a feedback loop model. An overview of the proposed approach is illustrated in Fig. 2.

The proposed approach can be described in detail as follows. Given an image I_0, the initial local phase coherence estimate P_0 is obtained at iteration $t = 0$. At each iteration t of the proposed estimation approach, the maximum moment of local phase coherence ϖ_t is computed using the following expression:

$$\frac{1}{2}\sum_\theta P_{t-1}(\underline{x},\theta)^2 + \frac{1}{2}\sqrt{4\left(\sum_\theta \left(P_{t-1}(\underline{x},\theta)\sin(\theta)\right)\left(P_{t-1}(\underline{x},\theta)\cos(\theta)\right)\right)^2 + \left(\sum_\theta \left[\left(P_{t-1}(\underline{x},\theta)\cos(\theta)\right)^2 - \left(P_{t-1}(\underline{x},\theta)\sin(\theta)\right)^2\right]\right)^2} \tag{5}$$

where $P_{t-1}(\underline{x},\theta)$ is the local phase coherence at iteration $t-1$ and orientation θ. What this effectively does is aggregate the local phase coherence at different orientations into a single measure of local phase coherence that accounts for local phase coherence variations due to orientation. A high

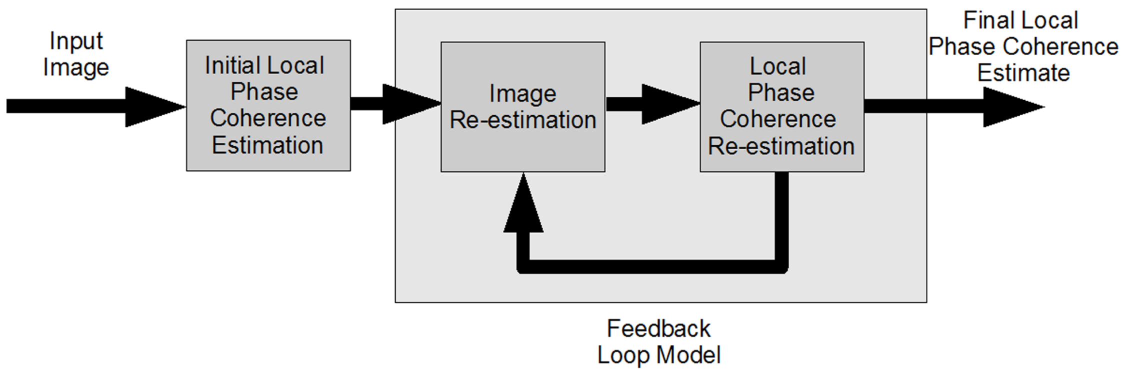

Figure 2. Overview of the proposed approach to local phase coherence estimation: First, an initial estimate of local phase coherence is performed and used as the input of the feedback loop. In the feedback loop, a new image estimate is computed based on the initial local phase coherence and used to re-estimate the local phase coherence. The re-estimated local phase coherence is then fed back and used to re-estimate the image. This is performed over multiple iterations to refine both the local phase coherence estimate and the image estimate. The final local phase coherence estimate is outputted after reaching the desired number of iterations.

value of ϖ_t at at point indicates that it possesses high structural significance within the image.

Once the maximum moment of local phase coherence ϖ_t has been computed, a new estimate of the image I_t is computed using a moment-adaptive bilateral estimation approach. In the bilateral estimation method, the estimated value at a point $\underline{x}$ is computed as the non-linearly weighted mean of the values at neighboring points. The non-linear weighing function used in the bilaterial estimation approach is defined by both the spatial relationship as well as the amplitudinal relationship between $\underline{x}$ and its neighboring points. As such, the bilateral estimation method enforces both spatial and amplitudinal locality. Using the Gaussian distribution as the basis for the bilateral estimation approach, the non-linear weighing function used in the bilateral estimation method can be defined as follows:

$$w(\underline{x},\psi) = w_a(\underline{x},\psi)w_s(\underline{x},\psi) \tag{6}$$

where

$$w_s(\underline{x},\psi) = e^{-\frac{1}{2}\left(\frac{\|\underline{x}-\psi\|}{\sigma_s}\right)^2} \tag{7}$$

$$w_a(\underline{x},\psi) = e^{-\frac{1}{2}\left(\frac{\|I(\underline{x})-I(\psi)\|}{\sigma_a}\right)^2} \tag{8}$$

and ψ denotes a neighborhood around point $\underline{x}$. The estimated value at x, denoted $\hat{I}$, can be computed as follows:

$$\hat{I}(\underline{x}) = \frac{\sum\limits_{\psi} w(\underline{x},\psi)I(\psi)}{\sum\limits_{\psi} w(\underline{x},\psi)} \tag{9}$$

The main advantage of the bilateral estimation method is that, by enforcing both spatial and amplitudinal locality at the same time, amplitudinal variations that are consistent with its neighboring points are preserved while inconsistent amplitudinal variations that are characteristic of noise are smoothed away. An important issue that must be considered when using the bilateral estimation method is the need to choose appropriate values for the constraint parameters σ_s and σ_a. To address this issue, the constraint parameters used in the image content estimation process are adapted based on the maximum moment of local phase coherence. This moment-adaptive approach to bilateral estimation was first proposed in [11]. In the proposed approach, we extend the concept of moment-adaptive bilateral estimation into an iterative approach, where local phase coherence and the underlying image content are re-estimated in a feedback loop process.

Given the maximum moment of local phase coherence ϖ_t, an estimate of the image I_t can be computed as follows:

$$I_t(\underline{x}) = \frac{\sum\limits_{\psi} w(\underline{x},\psi,\varpi_t(\underline{x}))I_{t-1}(\psi)}{\sum\limits_{\psi} w(\underline{x},\psi,\varpi_t(\underline{x}))} \tag{10}$$

where

$$w(\underline{x},\psi,\varpi_t(\underline{x})) = w_a(\underline{x},\psi,\varpi_t(\underline{x}))w_s(\underline{x},\psi,\varpi_t(\underline{x})) \tag{11}$$

$$w_s(\underline{x},\psi,\varpi_t(\underline{x})) = e^{-\frac{1}{2}\left(\frac{\|\underline{x}-\psi\|}{\sigma_s(\varpi_t(\underline{x}))}\right)^2} \tag{12}$$

$$w_a(\underline{x}, \psi, \varpi_t(\underline{x})) = e^{-\frac{1}{2}\left(\frac{\|I(\underline{x}) - I(\psi)\|}{\sigma_a(\varpi_t(\underline{x}))}\right)^2} \tag{13}$$

and the moment-adaptive constraint parameters $\sigma_s(\varpi_t(\underline{x}))$ and $\sigma_a(\varpi_t(\underline{x}))$ are defined as:

$$\begin{aligned} &\sigma_s(\varpi_t(\underline{x})) = \sigma_{s,\min} + (1 - \varpi_t(\underline{x}))^2 \left(\sigma_{s,\max} - \sigma_{s,\min}\right), \\ &\sigma_{s,\min} \leq \sigma_s \leq \sigma_{s,\max} \\ &\sigma_a(\varpi_t(\underline{x})) = \sigma_{a,\min} + (1 - \varpi_t(\underline{x}))^2 \left(\sigma_{a,\max} - \sigma_{a,\min}\right), \\ &\sigma_{a,\min} \leq \sigma_a \leq \sigma_{a,\max} \end{aligned} \tag{14}$$

Finally, based on the re-estimated image content I_t, the local amplitude and phase A_t and ϕ_t is computed and the local phase coherence ϕ_t is re-estimated as follows:

$$P_t(\underline{x}, \theta) = \frac{\sum\limits_n W(\underline{x}, \theta) \left\lfloor A_{n,t}\left(\underline{x}, \theta\right) \Delta\Phi(\underline{x}, \theta) - T \right\rfloor}{\sum\limits_n A_{n,t}\left(\underline{x}, \theta\right) + \varepsilon} \tag{15}$$

$$\Delta\Phi(\underline{x}, \theta) = \cos\left(\phi_{n,t}\left(\underline{x}, \theta\right) - \bar{\phi}_t\left(\underline{x}, \theta\right)\right) - \left|\sin\left(\phi_{n,t}\left(\underline{x}, \theta\right) - \bar{\phi}_t\left(\underline{x}, \theta\right)\right)\right| \tag{16}$$

where $A_{n,t}$ and $\phi_{n,t}$ are the amplitude and phase for wavelet scale n at iteration t respectively, W represents the frequency spread weighting factor, $\bar{\phi}_t$ represents the weighted mean phase at iteration t, T represents the noise threshold and ε is a small constant used to avoid division by zero. Once the new estimate of local phase coherence is obtained, the process is repeated until the desired number of iterations is achieved. During testing, it was found that four iterations was sufficient for providing good local phase coherence estimates in the presence of high image noise levels.

(a)

(b)

Figure 1. Effect of high image noise on local phase coherence: a) Noisy image ($\sigma = 81$, PSNR=10.35 dB), b) Maximum moment of local phase coherence

4 Experimental Results

To test the effectiveness of the proposed approach in improving the quality of local phase coherence estimates, a test set of five images were used. Each test image is first contaminated with high levels of white Gaussian noise and then process through the proposed method for four iterations. The initial estimate of local phase coherence, as it would appear if current approaches to local phase coherence estimation was used, is provided for comparison purposes. The local phase coherence estimates at various iterations are shown in Figure 3, Figure 4, Figure 5, Figure 6, and Figure 7. It is important to note that the local phase coherence estimates are visualized using the maximum moment of local phase coherence given the fact that local phase coherence is computed for multiple orientations. It can be observed that the proposed method produces local phase coherence estimates that provide noticeably improved structural information compared to the initial estimate, despite the high level of image noise. This is very important for computer vision applications that rely on structural information, such as structure-based segmentation and classification. It can also be observed that the quality of the local phase estimates improved as the number of iterations increased. This demonstrates that the proposed iterative approach to local phase coherence estimation can be used effectively to provide improved local phase coherence estimates.

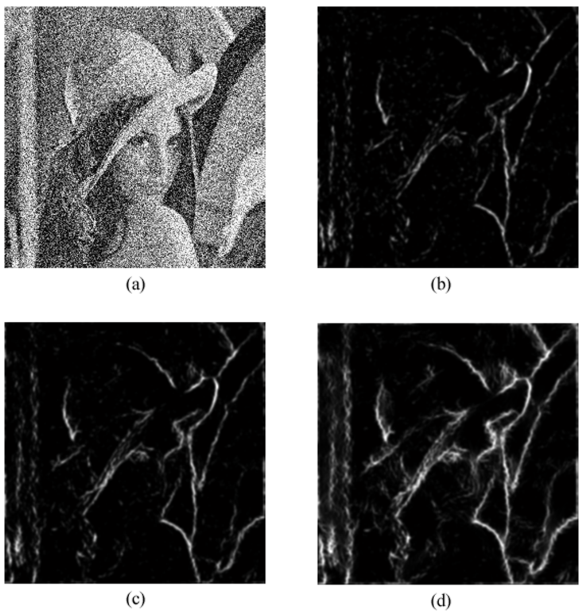

Figure 3. TEST1: a) Noisy image ($\sigma = 57$, PSNR=13.66 dB), and Maximum moment of local phase coherence after b) 0 iterations, c) 2 iterations, and d) 4 iterations

5 Conclusions

This paper introduces a novel iterative approach to estimating local phase coherence in images contaminated by high noise levels. By re-estimating the local phase coherence as well as the underlying image content iteratively using a feedback loop model, it was demonstrated that noticeably improved local phase coherence estimates can be obtained in situations characterized by low signal-to-noise ratios. Future work includes the investigation of different weighing functions for the image re-estimation process, as well as an adaptive approach for setting the termination criteria for the feedback loop process.

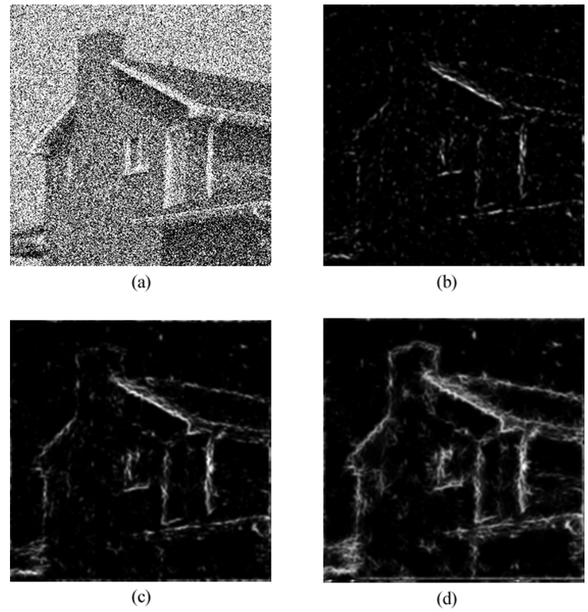

Figure 4. TEST2: a) Noisy image ($\sigma = 81$, PSNR=11.37 dB), Maximum moment of local phase coherence after b) 0 iterations, c) 2 iterations, and d) 4 iterations

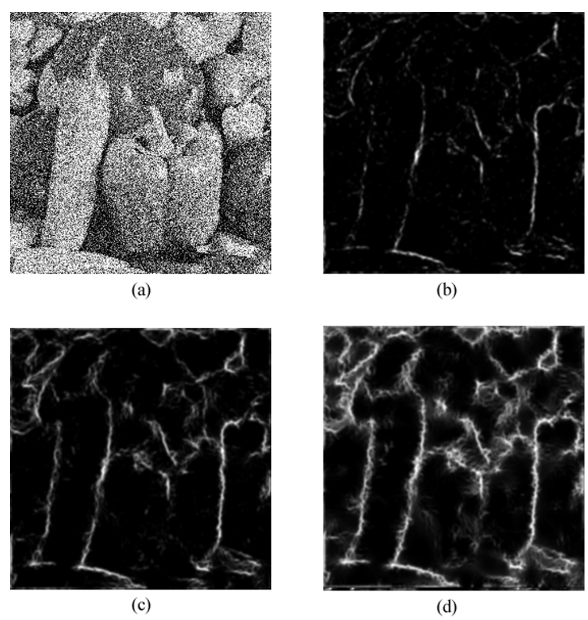

Figure 5. TEST3: a) Noisy image ($\sigma = 81$, PSNR=11.42 dB), Maximum moment of local phase coherence after b) 0 iterations, c) 2 iterations, and d) 4 iterations

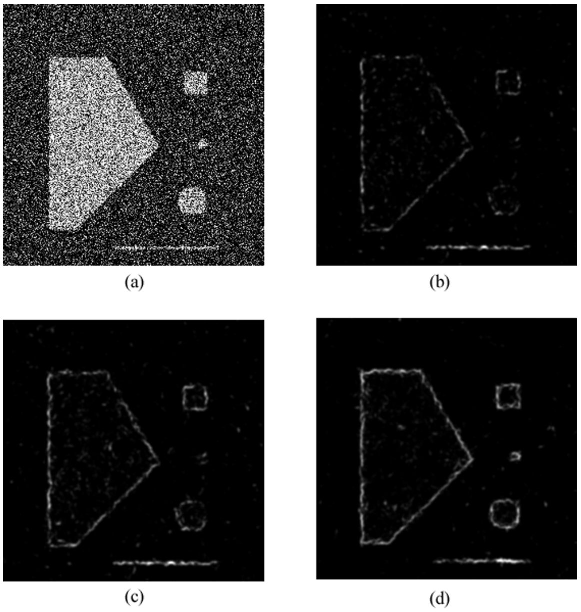

Figure 6. TEST4: a) Noisy image ($\sigma = 99$, PSNR=10.99 dB), and Maximum moment of local phase coherence after b) 0 iterations, c) 2 iterations, and d) 4 iterations

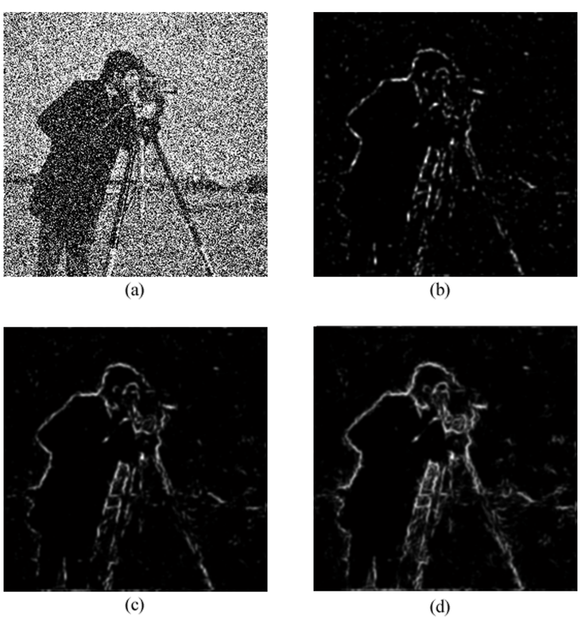

Figure 7. TEST5: a) Noisy image ($\sigma = 81$, PSNR=10.83 dB), and Maximum moment of local phase coherence after b) 0 iterations, c) 2 iterations, and d) 4 iterations

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