Line Extraction via Phase Congruency with a Novel Adaptive Scale Selection for Poisson Noisy Images

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ABSTRACT: In this paper we address the problem of extracting curvilinear structures from images in the presence of Poisson-distributed noise that is typically found in low-quality, low-contrast data, as well as in numerous medical imaging modalities. A contrast-robust phase congruency estimation method is proposed such that the optimal range of scales is selected in an adaptive manner for each location in the image. The adaptive regime is driven by a statistically well-principled variance test statistic which is based upon a local measure of the dispersion index. Experimental validation confirms that the adaptive scheme delivers superior line extraction results on mammographic imagery when compared to other recent attempts including the non-adaptive phase congruency.

1 INTRODUCTION

The extraction of lines and curvilinear structures (CLS) from noisy and cluttered imagery is one of the fundamental problems in pattern recognition. Myriad applications rely on accurate extraction of lines or line-like features either as an end goal in itself or as a means to support other image processing tasks. Curvilinear extraction can pose serious challenges when the analysed imagery is affected by strong noise or when the image is cluttered by objects that do not contain useful line features (Lee and Kweon 1997). A particularly difficult line detection problem arises when the imagery contains CLS at various scales and when these features overlap. This can happen as the result of 3D-data projection, which is often the case of medical scans. These images typically contain multiple occlusion and superposition artefacts, due to overlaps of features at different layers of tissue.

Recent decades have seen much, and continued, interest in the design of line and CLS detection methods and various different line-models and assumptions have evolved. Notable multi-scale techniques have been designed based on directionally adaptive transforms such as steerable filters (Jacob and Unser 2004), contourlets (da Cunha et al. 2006), feature-adapted beamlets (Berlemont and Olivo-Marin 2010), and curvelets (Ma and Plonka 2010). In contrast stochastic geometry approaches proceed by randomly sampling line elements and propagating them in such a way as to take into account the line-object interactions, e.g. in (Verdier and Lafarge 2014). At a steep computational complexity price, this allows one to take a far more adaptive and flexible approach which can accommodate various CLS properties by suitable design of prior energy terms. Other approaches combine elements of various extraction techniques, like isotropic non-linear filtering (Liu et al. 2007), space-scale line profile analysis (Steger 1998), skeleton extraction (Jang and Hong 2002), local Radon maximization (Krylov and Nelson 2014). Specialized line detection techniques have been adopted in various application domains, such as remote sensing (Verdier and Lafarge 2014), medical imaging (Obara et al. 2012), biometrical applications (Huang et al. 2008). Often CLS detection is a necessary preprocessing stage to extract complex objects that are comprised of distinct combinations of linear features, such as, e.g., spicule patterns that often surround malignant masses in mammographic images (Sampat et al. 2008, Muralidhar et al. 2010).

In this paper we focus on the scenario of images affected by Poisson-distributed noise, whereas
the majority of existing state-of-the-art methods explicitly or implicitly operate under the noise Gaussianity assumption. The Poisson distribution is characterized by one parameter, referred to as intensity, and both the distribution’s mean and variance are equal to its value. The corresponding noising model is particularly appropriate for discretized, positive-value data and characterizes several widely used image modalities, including low-light and low-quality sensor data, astronomy imagery, and many kinds of medical imagery (Gravel et al. 2004), such as, mammographic, X-ray, PET, SPECT, fluorescent confocal microscopy imaging, etc.

Along with the degradation of the analysed imagery by the Poisson noise, we also assume the presence of CLS at different scales, with possible occlusions and superpositions. In order to address the line extraction on such imagery, we will assume that the CLS of interest manifest as image ridges, i.e., smooth elongated curves, whose points are local maxima in at least one direction. Typically, these maxima are identified by resorting to local gradient information (Canny 1986, Lindeberg 1998). In this work we will, instead, employ the phase congruency characteristic, which evaluates the arrangement of phases of the signal at different frequencies and has an advantage of being stable under translation, geometric deformations and contrast variations (Kovesi 2003). This advantage is of significance for various types of imagery, especially in case when some of the relevant CLS demonstrate very weak contrast. In order to extract the phases, we will employ the directional Gabor filters, see (Kovesi 2003).

Since we assume that the imagery is inherently multiscale, the linear features can be superimposed one on top of the other. As a result, this can significantly interfere with the phase congruency estimation which requires non-cluttered line features. To tackle this problem we adaptively identify the optimal range of scales. Unlike (Schenk and Brady 2003), we propose an automatic adaptive scheme that is statistically well-founded in that it is based upon the dispersion index—an oft-utilised goodness-of-fit measure in statistical estimation of Poisson distributions (Karlis and Xekalaki 2000). The dispersion index allows to evaluate the degree of homogeneity of the Poisson-noisy image, and, thus, helps to identify the scale at which the local Gabor filter encounters an edge. Note that the employed adaptive scale selection approach is consistent with the scale-space edge concept defined in (Lindeberg 1998), according to which, the features represent connected sets of points characterized by some measure that persists over a consecutive range of scales.

The contribution of this work lies in the design of dispersion index-based automatic algorithm for adaptive optimal scales identification to extract CLS using phase congruency on Poisson-noisy images. The experimental validation is performed on mammographic images, where CLS extraction supports an array of important tasks such as coregistration or inference regarding tissue malformation or pathology (Muralidhar et al. 2010).

The rest of the paper is arranged as follows. In Section 2 we recall the employed concepts of phase congruency and Gabor filtering. In Section 3 we design a novel scale selection approach for the Poisson-noisy imagery. In Section 4 we report experiments, and in Section 5 we draw the conclusions.

2 PHASE CONGRUENCY AND GABOR FILTERING

Phase congruency exploits the expected behaviour of the image line- and edge-like features in the frequency domain (Kovesi 2003). In particular, the frequency components of such features share similar phases—e.g., observe the behaviour of the square wave frequency components at points \{-1, 0, 1\} corresponding to the edges in Fig. 1(a). The phase congruency concept disregards the amplitudes of the frequency components and, similarly to coherence, analyses solely the phase information.

The phase congruency measurement procedure at a signal point is exemplified geometrically in Fig. 1(b). The Fourier components in the analysed signal have amplitudes \(C_n\) and phase angles \(\gamma_n\); the magnitude of the sum vector is the local energy \(E\). The phase congruency at point \(z\) is classically defined as \(PC(z) = |E(z)|/\sum_n C_n(z)\). In this paper we will employ a slightly different definition of phase congruency that allows a better localization (Kovesi 2003):

\[
PC = \frac{\sum_n C_n(z) \max[0, \alpha_n(z)]}{\sum_n C_n(z)},
\]

where \(\alpha_n(z) = \cos(\gamma_n(z) - \bar{\gamma}(x)) - |\sin(\gamma_n(z) - \bar{\gamma}(x))|\). Instead of resorting to the Fourier transform, the local frequency information is obtained via banks of Gabor filters tuned to different spatial frequencies (Kovesi 2003).

Gabor filters have received considerable attention because they have an analytical expression in both time and frequency, are easy to implement, and are highly tunable. It has also been argued that the filters resemble the behaviour of certain cells in the visual cortex of mammals (Serre et al. 2005). We use these filters here as a means to estimate the time-frequency coefficients necessary for the estimation of phase congruency. Other wavelet bases could be used in their place instead, however the choice of wavelet is beyond the scope of this
work. A Gabor filter is defined as providing an impulse response equal to a harmonic function multiplied by a Gaussian function. In the frequency domain its filtering function can be written as

\[
\Psi(u, v) = \frac{1}{2\pi \sigma_u \sigma_v} \exp\left\{ -\frac{(u - u_0)^2}{2\sigma_u^2} - \frac{(v - v_0)^2}{2\sigma_v^2} \right\},
\]

with \( \sigma_u = 1/(2\pi \sigma_x) \), \( \sigma_u = 1/(2\pi \sigma_y) \), and \( \sigma_x, \sigma_y \) - the standard deviations in the time domain. The Gabor filter can be thought of as a Gaussian function shifted in frequency to position \((u_0, v_0)\) at orientation \( \tan^{-1}\frac{u_0}{v_0} \), see Fig. 2. In this paper the Gabor filters are convolved with the signal at \( \mathcal{S} \) distinct scales and \( \mathcal{O} \) uniformly spread orientations.

The Gabor filters have been successfully used for various image processing applications (Kovesi 2003, Serre et al. 2005, Teuner et al. 1995). In particular, in case of Poisson-noisy images in (Buciu and Gacsadi 2011) the Gabor wavelets were reported as an efficient tool for directional feature analysis for mammographic imagery. Nevertheless, one of the conclusions in the study was that high frequency image components are rather sensitive to the Poisson noise.

3 ADAPTIVE SCALE SELECTION

Consider imagery affected by Poisson noise. Unlike additive Gaussian noise (which is the limit case for Poisson noise (Lehmann and Romano 2005)), it is signal-dependent. This can make separating signal from noise a difficult task. Assume that some image area depicts a constant signal affected by noise—this means that the data will be Poisson-distributed with intensity \( \lambda \) equal to the pure signal intensity (Gravel et al. 2004). The purpose of adaptive scale selection is at every image point to identify the resolution at which this point is no longer contained inside a homogeneous area.

In other words, to identify the minimum scale \( s^* \) where the neighbourhood of the given pixel includes the Poisson-distributed values with distinct intensity parameters, i.e., multiple sample populations are represented in this neighbourhood characterised by distinct Poisson distributions.

To estimate \( s^* \) we employ the dispersion index, which is a widely used tool to construct goodness-of-fit tests and analyse the homogeneity property of the Poisson distribution (Karlis and Xekalaki 2000). The dispersion index, also called variance-to-mean ratio, is defined as \( D = \sigma^2/\mu \), with variance \( \sigma^2 \) and mean value \( \mu \). It is immediate, that the Poisson distribution is characterised by \( D = 1 \).

In order to employ the dispersion index to test the homogeneity of a sample of \( N \) random observations \( \{X_i\}_{i=1}^N \), we employ the variance test (VT) statistic (Karlis and Xekalaki 2000) defined as

\[
VT = \frac{\sum_{i=1}^N (X_i - \bar{X})^2}{X \sqrt{2N}} - \sqrt{\frac{N}{2}},
\]

with the sample mean \( \bar{X} = \frac{\sum_{i=1}^N X_i}{N} \). This statistic constitutes the locally most powerful unbiased test for the Poisson homogeneity hypothesis \( \{H_0 : \lambda_1 = \ldots = \lambda_N\} \) against the mixed Poisson alternative \( \{H_A : \exists m : 1 < m \leq N, \lambda_1 \neq \lambda_m\} \).

It is immediate that this alternative hypothesis definition corresponds exactly to the specified above region homogeneity specification. The value of VT is a slight modification of the dispersion index, which is obtained by introducing a correction with respect to the sample size \( N \). The values of the VT statistic are standard normal distributed (Karlis and Xekalaki 2000) under \( H_0 \).

In this paper we employ the Gabor filters to evaluate the phase congruency, and, therefore, we will use the VT on the samples originating from inside the ellipses construced according to the levels of filter responses in square magnitude - from 0.5 to 1, see Fig. 2. Thus, for every scale \( s = 1, \ldots, \mathcal{S} \) and orientation \( o = 1, \ldots, \mathcal{O} \) we retrieve a data sample.
of size $N_{so}$. For each of these samples we calculate the corresponding value of the sample dispersion index $VT_{so}$. Our target is to select the optimal scale $s^*$ such that the deviation of the $VT_{so}$ from the standard normal distribution is meaningful. At every scale we calculate $\mathcal{O}$ distinct values of the variance test and then average over the different orientations because (i) we do not aim to identify the optimal orientation in this procedure, and (ii) the averaging improves robustness with respect to the signal fluctuations. Summarizing the above, the optimal scale can be identified as

$$s^* = \arg \max_{s=1,...,S} \sum_{o=1}^{\mathcal{O}} |VT_{so}|/\mathcal{O}.$$  

In the experimental study we do not assign statistical test meaning to the $VT$ values, due to a high variability of confidence levels obtained with the test. This observed variability can be explained by the employed two simplifying assumptions: (i) pixel independence and (ii) constant-intensity signal in the homogeneous zones. Nevertheless, the experiments suggest that at a certain scale a substantial increase of $VT$ is typically observed, and we will use this behaviour as an indicator to obtain the scale estimates. Specifically, we will set

$$s^* = \arg \max_{s=2,...,S} \sum_{o=1}^{\mathcal{O}} |VT_{so}|/\sum_{o=1}^{\mathcal{O}} |VT_{s-1,o}|.$$  

After having identified for every pixel the optimal scale $s^*$, we perform phase congruency-based edge extraction as in Eq. (1) using scales \{s, \ldots, \min(s + \Delta s, S)\}. It is worth noting that in order to benefit from adaptive scale selection, $\Delta s$ should be set with a small value, we suggest using $\Delta s \leq 4$. Once the features are extracted, it is necessary to pick the bright ridges from all the line- and edge-like features. To do so we propose to multiply the extracted $PC$ values by the factor $\max^{2}[0, 2\tilde{\gamma}/\pi]$, where $\tilde{\gamma}$ is the pixel weighted mean phase (corresponding to the magnitude $E$, see Fig. 1(b)). This manipulation removes all the dark lines and edges (with $-\pi/2 \leq \tilde{\gamma} \leq 0$), and penalizes the less distinct non-symmetric bright line features ($0 < \tilde{\gamma} < \pi/2$). Finally, a hard thresholding could be employed to obtain a binary CLS map.

4 EXPERIMENTAL VALIDATION

In this section we report experiments on mammographic images from the Digital Database for Screening Mammography (Heath et al. 2001). We have selected the number of scales $S = 8$ and consider $\mathcal{O} = 16$ orientations. The choice of the latter parameter is not significant as long as it is big enough ($\mathcal{O} > 8$), the former is selected with respect to the CLS present, but in the general case should not be small. The scale range parameter $\Delta s$ was set equal to 3.

The results on three typical mammographic regions of interest are demonstrated in Fig. 3. Note that except for thresholding by the mean $PC$ value for every set of pixels extracted at the same scale $s^*$, we report the raw results, without resorting to image morphology tools, that can improve the visual quality, nor do we discard any scales, which is an option if the CLS are a priori expected at some particular scales. We observe that the scale maps are informative on their own and contain the CLS, which are visible as regions with the adaptive scale different from the surrounding background’s scale. By construction the designed method is local and can be successfully applied to non-stationary imagery that contains regions characterized by distinct statistical properties. The scale maps (after appropriate smoothing) can be employed as an indicator to distinguish between different layers of the low-fibroglandularity tissue on the mammograms.

The designed method demonstrates an ability to automatically adapt the scale such that, on the one hand, the blob in the top image in Fig. 3 is separated from some of the CLS but, on the other hand, the higher scale (red) line on the right half of the image is clearly distinguished from the neighboring low scale CLS. Likewise, in the second image the finer line structures are extracted against the slightly coarser scale content of the fibroglandular tissue more clearly than by the other methods. The third mammogram demonstrates a high variety of CLS at different scales and various levels of occlusion in the tissue. The designed method performs well with higher scale (finer) features but confuses some low scale features.

In Fig. 3 we present results obtained with three benchmark methods. Comparison between the standard phase congruency extractor (based on global manual setting of scales) and the proposed
method demonstrates a substantially stronger capacity of the latter to extract multiscale features. Comparing with the Radon-based enhancement method (Sampat et al. 2008) reveals the contrast dependence of the latter and its weaker performance in modeling different scale features. As compared with a primitive-based monoscale method (Krylov and Nelson 2014), the proposed approach produces noisier but also more CLS-sensitive maps. The designed method can be used to reduce the parametric initialization in (Krylov and Nelson 2014) and address the multiscale line-features.

In Fig. 4 we demonstrate the performance of the scale selection based on $s^*$ at several image points and visualize the process of the final map construction as a sum of phase congruency components extracted at adaptively estimated scales. It can be seen how CLS of different scales contribute to the final line-detection map.

5 CONCLUSIONS

We have proposed a novel automatic approach to address the problem of multiscale CLS extraction from Poisson-noisy images. This approach employs the phase congruency principle and performs the adaptive scale selection for the phase extraction. The latter is performed in a statistically well-founded way by employing the variation test statistic based on the dispersion index value. We thus formulate an application-independent Poisson-noise specific technique, which in this respect is unlike the majority of existing state-of-the-art methods that typically target the Gaussian noise. The proposed line detection method has been experimentally validated and compared with benchmark methods on mammographic images.

The principal direction for future development is in designing of primitive-based multiscale CLS extraction techniques that could benefit from the pixel-based result and scale selection procedure designed in this study, e.g., by integration with local Radon transforms (Krylov and Nelson 2014), active contours (Muralidhar et al. 2010), etc.

REFERENCES


