

Multiscale Particle Filter through Contour Detection Framework

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Abstract: We focus on the edgelets by detecting the algorithm by joining two small pieces of edges through contour detection. Bayesian modeling focus on multiscale edgelets which is embeds semi-local information. Prior and distributions can be seen offline with the help of shape database. One can see the following features online like integrate color and gradient information via local, textural, oriented, and profile gradient-based features for understanding and comparing. The underlying model is estimated using a sequential Monte Carlo approach, and the final soft contour detection map is retrieved from the approximated trajectory distribution. We also propose to extend the model to the interactive cut-out task. Experiments conducted on the Berkeley Segmentation data sets show that the proposed MultiScale Particle Filter Contour Detector method performs well compared to competing state-of-the-art methods.

Keywords: Particle filtering, sequential Monte Carlo methods, statistical model, multiscale contour detection, BSDS

1. Introduction

Detecting contours is an ubiquitous task in image processing, as it is often the basis of higher level applications, such as segmentation, recognition, tracking, etc. The intrinsic variability of natural images makes this task a proper challenge. In this paper, we define a contour as a visually salient, well-defined chain of connected pixels. This definition may be interpreted in terms of the Gestalt Theory, which underlines the importance of perceptual grouping and continuation properties for human visual perception. Also, saliency is contextual, suggesting that it conforms the Helmholtz principle, which confers more importance to rare geometric patterns. Properties of good continuation and saliency shall serve as motivations of the proposed contour detector. A connected pixel set is the atomic element of the proposed method, and is called an edgelet. This term shall not be mistaken with the edgelet transform (an image representation method), however, our definition is similar to the ones in [1], [2]. The structure of an edgelet is learned offline using a shape database. This results in the modeling of an empirical prior distribution. This choice differs from contour detection approaches integrating a prior information by imposing a potentially restrictive mathematical model.

The contextual visual saliency is learned online using tail distributions, notably employed in the a contrario framework proposed by Desolneux et al. [3]. The associated likelihoods integrate image feature statistics to be adaptive to the image and hence get high responses only on perceptually significant contours. We also want to express the bounds between the edgelets, reflecting the continuity principle of the Gestalt Theory. This can be done in a Markovian modeling fashion by defining a spatial transition model between consecutive edgelets. Prior, transition, and likelihoods models are the basic ingredients of Sequential Monte Carlo methods. Among those, it turns out that particle filtering techniques are particularly well-suited for estimating these kinds of recursive distributions. This is not the first attempt to use a particle filtering technique to

extract contours. In 2001, Perez et al. [4] proposed the JetStream, a well-known algorithm that retrieves one contour curve from an image by tracking points locally at a fixed step length. The authors proposed a semi-automatic routine to extract complex contours by allowing the user to constrain the contour path. This approach is useful for the interactive cut-out task, but by nature, can hardly be applied to the challenging problem of automatic contour detection. Other particle filtering techniques have been used in the context of vessels and arteries detection in 3D CT data [5], [6]. Like the JetStream algorithm, these techniques have been mainly dedicated for semi-automatic and/or single detection tasks. Contrary to the aforementioned methods, our particle filtering framework is fully automatic, semi-local, and contextually-dependent. Moreover, compared to our preliminary model [7], the edgelets are defined at two scales, meaning that the algorithm locally tracks the edgelets along contours by sequentially operating the computations on each scale. This yields to our new MultiScale Particle Filter Contour Detector (MS-PFCD).

2. Literature Survey

Jian Sun et al said in their work Gradient Profile Prior and Its Applications in Image Super-Resolution and Enhancement [32] that the novel generic image prior—gradient profile prior, which implies the prior knowledge of natural image gradients. In this prior, the image gradients are represented by gradient profiles, which are 1-D profiles of gradient magnitudes perpendicular to image structures. We model the gradient profiles by a parametric gradient profile model. Using this model, the prior knowledge of the gradient profiles are learned from a large collection of natural images, which are called gradient profile prior. Based on this prior, we propose a gradient field transformation to constrain the gradient fields of the high resolution image and the enhanced image when performing single image super-resolution and sharpness enhancement. With this simple but very effective approach, we are able to produce state-of-the-art results. The reconstructed high

resolution images or the enhanced images are sharp while have rare ringing or jaggy artifacts.

David R. Martin, et al worked in their paper Learning to Detect Natural Image Boundaries Using Local Brightness, Color, and Texture Cues [33] and said that The goal of this work is to accurately detect and localize boundaries in natural scenes using local image measurements. We formulate features that respond to characteristic changes in brightness, color, and texture associated with natural boundaries. In order to combine the information from these features in an optimal way, we train a classifier using human labeled images as ground truth. The output of this classifier provides the posterior probability of a boundary at each image location and orientation. We present precision-recall curves showing that the resulting detector significantly outperforms existing approaches. Our two main results are 1) that cue combination can be performed adequately with a simple linear model and 2) that a proper, explicit treatment of texture is required to detect boundaries in natural images. Nicolas Widynski, et al said in their work A Contrario Edge Detection with Edgelets [34] that the Edge detection remains an active problem in the image processing community, because of the high complexity of natural images. In the last decade, Desolneux et al. proposed a novel parameter free detection approach, based on the Helmholtz principle. Applied to the edge detection problem, this means that observing a true edge in random and independent conditions is very unlikely, thus, such events are considered meaningful. However, overdetection may occur, partly due to the use of a single pixel-wise feature. In this paper, we propose to introduce higher level information in the a contrario framework, by computing several features along a set of connected pixels (an edgelet). Among the features, we introduce a shape prior, learned on a database. We propose to estimate the a contrario distributions of the two other features, namely the gradient and the texture, by a Monte-Carlo simulation approach. Experiments show that our method improves the original one, by decreasing the number of non relevant edges while preserving the others.

Michael Maire et al said in their work Using Contours to Detect and Localize Junctions in Natural Images [35] Contours and junctions are important cues for perceptual organization and shape recognition. Detecting junctions locally has proved problematic because the image intensity surface is confusing in the neighborhood of a junction. Edge detectors also do not perform well near junctions. Current leading approaches to junction detection, such as the Harris operator, are based on 2D variation in the intensity signal. However, a drawback of this strategy is that it confuses textured regions with junctions. We believe that the right approach to junction detection should take advantage of the contours that are incident at a junction; contours themselves can be detected by processes that use more global approaches. In this paper, we develop a new high-performance contour detector using a combination of local and global cues. This contour detector provides the best performance to date ($F=0.70$) on the Berkeley Segmentation Dataset (BSDS) benchmark. From the resulting contours, we detect and localize candidate junctions, taking into account both contour salience and geometric configuration.

3. Methodology

For using a new retrieval images we use local diagonal extrema patterns with HSV colour space. HSV colour space is a technique which helps in increasing the color, intensity and brightness of images. Local extrema patterns are applied to define the local information of images and gray level co occurrence pattern extracts the local directional information from the local extreme pattern and then converts into well organized vector features with the use of gray level co occurrence matrix. This method is tested on various databases like Corel (Corel 1K, Corel 5K, Corel 10K), MIT, VisTex and STex.

4. Results and Discussion

All the matters and the parameters has been learned using a gradient ascent on the F-measure on the training data set of the BSDS300. The length of an edgelet at the coarse scale has been found optimal at $Me = 3$ (with a 4-connexity neighborhood). The number of samples in the learning procedures must be large enough to obtain a good approximation of the respective distributions, depending on the length of an edgelet. We set $Sp = 2 \times 10^6$ for the prior, $St = 10^5$ for the transition, $Sf = 10^6$ for the features and $Sie = 1.5 \times 10^5$ and $Sie = 15$ for the initialization distributions. Results obtained with edgelets of greater lengths, i.e., $Me = 4$, and $Me = 5$, showed a slight decline in the F-measure scores, while requiring considerably more samples (Sp and St) to be estimated. This can be attributed to the increase of the dimensionality that imposes more particles to estimate the trajectory distribution. For the observation model, we compute the textural gradient using a histogram of $R = 5 \times 5 \times 125$ bins. For this feature, the image is defined on the CIE Lab colorspace. The number of bins by orientation R_m for the oriented gradient feature is 10. In order to consider enough points to create the histograms, the length of each side of the normal segment is set to 11 pixels, with a line width of 5. For the profile gradient, the parameters se and ke are respectively set to 0.7 and 1.6 and the profile is computed on a 5-pixel-long vector normal segment [24]. We use a mean for the fusion operators C , $_$, and J , and a min operator for F . The values of the feature multiplicative constants are set to $_1e = 5$, $_2e = 6$, $_3e = 2$, and $_4e = 16$ at the coarse scale, and set to $_1e = 5$, $_2e = 6$, $_3e = 3$, and $_4e = 16$ at the reference scale. The prior probability of jump b is set to 0.00015. The parameter $K = 200$ ensures the monotonical increase of the stopping criterion. Finally, a particle filter is stopped whenever its number of steps is greater than 150 and the proportion of its jumps g reach 0.137. We fix the total number of particles N to 5,625 to provide a good tradeoff between detection performance and computational cost.

We set the number of particle filters L to 75 in this number order to smooth the results of particles by filter NL is $5,625 = 75 \times 75$, which is enough to obtain a satisfying accuracy of each particle filter. Note that NL may impact on the stopping criteria: using a larger number of particles results in a slight reduction of g , although it does not compensate for the additional computational cost. We approximate N_q using a small number of samples $N_q = 50$.

Our MS-PFCD method performs well, with a FMeasure score at 0:70 (recall: 0:70, precision: 0:69) on the 100 test images of the BSDS300, and a F-Measure score at 0:72 (r: 0:73, p: 0:71) on the 200 test images of the BSDS500. Due to the stochastic nature of the algorithm, we performed the experiment 15 times and obtained a variance of 2:96 _ 10_7. Only the methods providing the three measures on either data set are reported. The first and most popular measure is the optimal data set scale (ODS) F-Measure score. It is obtained using the global optimal threshold on the data set. When no additional information is provided, this metric is simply referred to as the F-Measure score. The optimal image scale (OIS) is the F-Measure score obtained using the optimal threshold on each image. The last measure is the average precision (AP) and corresponds to the area under the precision-recall curves of Fig. 3. Both the precision-recall curves and the quantitative table results show that our MS-PFCD performs well compared to state-of-the-art contour detection methods, while it compares favorably to the reference method, i.e., the gPb, on the BSDS500. The difference is especially visible for the AP measure in both data sets.

Table 1: Comparing of the result obtained on the BSDS300 and the BSDS500

	BSDS300			BSDS500		
	ODS	OIS	AP	ODS	OIS	AP
HUMAN	0.79	0.79	-	0.80	0.80	-
MS-PFCD	0.70	0.71	0.71	0.72	0.74	0.74
SCG[17]	0.71	-	-	0.74	0.76	0.77
gPb[9]	0.70	0.72	0.66	0.71	0.74	0.65
PFCD[7]	0.68	0.69	0.67	0.70	0.72	0.69
Canny[30]	0.58	0.62	0.58	0.60	0.63	0.58

ODS is the optimal scale on the data set, OIS is the optimal scale on each image, and AP the average precision on the recall range.

5. Conclusion

We proposed a multiscale particle filter approach to track contours in complex natural images. The basic element of our model is a pair of edgelets, i.e., sets of connected pixels defined at two scales, that naturally embeds semi-local information. The underlying Bayesian model involves multiscale prior and transition distributions, which are learned on a shape database, and a multiscale likelihood component, which is adaptive to an image in order to retrieve only the most relevant contours. Experiments have been conducted on the Berkeley data sets and the proposed approach obtained competitive results with the state-of-the-art. We also extended our model for the interactive cut-out task. Qualitative results and reduced computational cost make of this method a practical tool. Possible improvements of this work include: more elaborated features, in agreement with other state-of-the-art methods; multiscale parametric edgelet distributions, that would possess the advantage of being independent from the image dimensions; and finally a more sophisticated strategy to maintain acceptable particle cloud diversity, in this case recent advances in the particle filtering literature might help

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