Computational Investigation of Feature Extraction and Image Organization

DISSERTATION

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ABSTRACT

This dissertation investigates computational issues of feature extraction and image organization at different levels. Boundary detection and segmentation are studied extensively for range, intensity, and texture images. We developed a range image segmentation system using a LEGION network based on a similarity measure consisting of estimated surface properties. We propose a nonlinear smoothing algorithm through local coupling structures, which exhibits distinctive temporal properties such as quick convergence.

We propose spectral histograms, consisting of marginal distributions of a chosen bank of filters, as a generic feature vector based on that early steps of human visual processing can be modeled using local spatial/frequency representations. Spectral histograms are studied extensively in texture modeling, classification, and segmentation. Experiments in texture synthesis and classification demonstrate that spectral histograms provide a sufficient and unified feature in capturing perceptual appearance of textures. Spectral histograms improve significantly the classification performance for challenging texture images. We also propose a model for texture discrimination based on spectral histograms which matches existing psychophysical data. A new energy functional for image segmentation is proposed. With given regional features, an iterative and deterministic algorithm for segmentation is derived. Satisfactory results
are obtained for natural texture images using spectral histograms. We also developed a novel algorithm which automatically identifies homogeneous texture features from input images. By incorporating texture structures, we achieve accurate texture boundary localization through a new distance measure. With extensive experiments, we demonstrate that spectral histograms provide a generic feature which can be used effectively to solve fundamental vision problems.

Based on a novel and biologically plausible boundary-pair representation, perceptual organization is studied. A network is developed which can simulate many perceptual phenomena through temporal dynamics. Boundary-pair representation provides a unified explanation of edge- and surface-based representations.

A prototype system for automated feature extraction from remote sensing images is developed. By combining the advantages of the learning-by-example method and a locally coupled network, a generic feature extraction system is feasible. The system is tested by extracting hydrographic features from large images of natural scenes.
In memory of my parents, Fu-Lu Liu and She-Zi Liu, who taught me values and knowledge silently.
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5.5 A row from the image shown in Figure 5.3 and the result using derived probability model. In (b) and (c), solid lines stand for left region and dashed lines stand for right region. (a) The 64th row from the image. (b) The probability of the two given regional features using asymmetric windows when estimating spectral histogram. The edge point is correctly located between columns 64 and 65. (c) Similar to (a) but using windows centered at the pixel to compute spectral histogram. Labels between columns 58 and 65 cannot be decided. This is because that the computed spectral histograms within that interval do not belong to either region.

5.6 Classification result based on $\chi^2$-statistic for the row shown in Figure 5.4(a). Solid lines stand for left region and dashed lines stand for right region. (a) $\chi^2$-statistic from the two given regional features using asymmetric windows when estimating spectral histogram. If we use the minimum distance classifier, the edge point will be located between columns 65 and 66, where the true edge point should be between columns 64 and 65. (b) Similar to (b) but using windows centered at the pixel to compute spectral histogram. The edge point is localized between 61 and 62.
5.7 Gray-level image segmentation using spectral histograms. \(W(s)\) is a 15 \(\times\) 15 square window, \(\lambda^G = 0.2\), and \(\lambda^B = 5\). Two features are given at \((32, 64)\) and \((96, 45)\). (a) A synthetic image with size 128 \(\times\) 128. The image is generated by adding zero-mean Gaussian noise with different \(\sigma\)'s at the two different regions. Here the boundary is 'S' shaped to test the segmentation algorithm in preserving boundaries. (b) Initial classification result. (c) Final segmentation result.

5.8 Texture image segmentation using spectral histograms. \(W(s)\) is a 29 \(\times\) 29 square window, \(\lambda^G = 0.2\), and \(\lambda^B = 2\). Features are given at pixels \((32, 32)\) and \((96, 32)\). (a) A texture image consisting of two texture regions with size 128 \(\times\) 64. (b) Initial classification result. (c) Final segmentation result.

5.9 Texture image segmentation using spectral histograms. \(W(s)\) is a 29 \(\times\) 29 square window, \(\lambda^G = 0.2\), and \(\lambda^B = 3\). (a) A texture image consisting of two texture regions with size 128 \(\times\) 64. (b) Initial classification result. (c) Final segmentation result.

5.10 Texture image segmentation using spectral histograms. \(W(s)\) is a 35 \(\times\) 35 square window, \(\lambda^G = 0.4\), and \(\lambda^B = 3\). Four features are given at \((32, 32)\), \((32, 96)\), \((96, 32)\), and \((96, 96)\). (a) A texture image consisting of four texture regions with size 128 \(\times\) 128. (b) Initial classification result. (c) Final segmentation result.

5.11 Texture image segmentation using spectral histograms. \(W(s)\) is a 35 \(\times\) 35 square window, \(\lambda^G = 0.4\), and \(\lambda^B = 3\). Four features are given at \((32, 32)\), \((32, 96)\), \((96, 32)\), and \((96, 96)\). (a) A texture image consisting of four texture regions with size 128 \(\times\) 128. (b) Initial classification result. (c) Final segmentation result.

5.12 Texture image segmentation using spectral histograms. \(W(s)\) is a 29 \(\times\) 29 square window, \(\lambda^G = 0.2\), and \(\lambda^B = 3\). Four features are given at \((32, 32)\), \((32, 96)\), \((96, 32)\), and \((96, 96)\). (a) A texture image consisting of four texture regions with size 128 \(\times\) 128. (b) Initial classification result. (c) Final segmentation result.
5.13 Texture image segmentation using spectral histograms. \( W^{(s)} \) is a \( 35 \times 35 \) square window, \( \lambda_F = 0.4 \), and \( \lambda_B = 3 \). Four features are given at \((32, 32), (32, 96), (96, 32), \) and \((96, 96)\). (a) A texture image consisting of four texture regions with size \( 128 \times 128 \). (b) Initial classification result. (c) Final segmentation result. 

5.14 A challenging example for texture image segmentation. \( W^{(s)} \) is a \( 35 \times 35 \) square window, \( \lambda_F = 0.4 \), and \( \lambda_B = 20 \). Two features are given at \((160, 160) \) and \((252, 250)\). (a) Input image consisting of two texture images, where the boundary can not be localized clearly because of their similarity. The size of the image is \( 320 \times 320 \) in pixels. (b) Initial classification result. (c) Final segmentation result.

5.15 Another challenging example for texture segmentation. \( W^{(s)} \) is a \( 35 \times 35 \) square window, \( \lambda_F = 0.4 \), and \( \lambda_B = 20 \). Two features are given at \((160, 160) \) and \((252, 250)\). (a) Input image consisting of two texture images, where the boundary can not be localized clearly because of their similarity. The size of the image is \( 320 \times 320 \) in pixels. (b) Initial classification result. (c) Final segmentation result.

5.16 Segmentation for a texton image with oriented short lines. \( W^{(s)} \) is a \( 35 \times 35 \) square window, \( \lambda_F = 0.4 \), and \( \lambda_B = 10 \). Two features are given at \((185, 67) \) and \((180, 224)\). (a) The input image with size of \( 402 \times 302 \) in pixels. (b) The initial classification result. (c) The segmentation result using spectral histograms. (d) The initial classification result using two Gabor filters \( G_{cos}(10, 30^\circ) \) and \( G_{cos}(10, 60^\circ) \). (e) The segmentation result using two Gabor filters. The result is improved significantly.

5.17 Segmentation results at different integration scales. Parameters \( \lambda_F = 0.4 \), and \( \lambda_B = 4 \) are fixed. (a) The input image. (b) The percentage of mis-classified pixels.

5.18 Segmentation results using different segmentation scales for the image shown in Figure 5.17(a). In each sub-figure, the left shows the initial classification result and the right shows the segmentation result. Parameters \( \lambda_F = 0.4 \), and \( \lambda_B = 4 \) are fixed. (a) \( W^{(s)} \) is a \( 1 \times 1 \) square window. (b) \( W^{(s)} \) is a \( 3 \times 3 \) square window. (c) \( W^{(s)} \) is a \( 5 \times 5 \) square window. (d) \( W^{(s)} \) is a \( 7 \times 7 \) square window.
5.19 A texture image with a cheetah. The feature vector is calculated at pixel (247, 129) at scale 19 × 19, λ_T = 0.2, and λ_B = 2.5. To demonstrate the accuracy of the results, the classification and segmentation results are embedded into the original image by lowering the intensity values of the background region by a factor of 2. (a) The input image with size 324 × 486. (b) The initial classification result using 8 filters. (c) The final segmentation result using 8 filters. (d) The initial classification result using 6 filters consisting of D_{xx}, D_{yy}, LoG(\sqrt{2}/2), LoG(1), LoG(2) and LoG(3). (e) The final segmentation result corresponding to (d)........................................... 154

5.20 An indoor image with a sofa. The feature vector is calculated at pixel (146, 169) at scale 35 × 35, λ_T = 0.2, and λ_B = 3. (a) Input image with size 512 × 512. (b) Initial classification result. (c) Final segmentation result. (d) Segmentation result if we assume there is another region feature given at (223, 38).......................... 155

5.21 Texture image segmentation with representative pixels identified automatically. W^{(s)} is a 29 × 29 square window, W^{(a)} is a 35 × 35 square window, λ_C = 0.1, λ_A = 0.2, λ_B = 2.0, λ_T = 0.2, and T_A = 0.08. (a) Input texture image, which is shown in Figure 5.8. (b) Initial classification result. Here the representative pixels are detected automatically. (c) Final segmentation result. ........................................... 158

5.22 Texture image segmentation with representative pixels identified automatically. W^{(s)} is a 29 × 29 square window, W^{(a)} is a 43 × 43 square window, λ_C = 0.4, λ_A = 0.4, λ_B = 5.0, λ_T = 0.4, and T_A = 0.30. (a) Input texture image, which is shown in Figure 5.10. (b) Initial classification result. Here the representative pixels are detected automatically. (c) Final segmentation result. ........................................... 158

5.23 Texture image segmentation with representative pixels identified automatically. W^{(s)} is a 29 × 29 square window, W^{(a)} is a 43 × 43 square window, λ_C = 0.1, λ_A = 0.2, λ_B = 5.0, λ_T = 0.4, and T_A = 0.20. (a) Input texture image, which is shown in Figure 5.11. (b) Initial classification result. Here the representative pixels are detected automatically. (c) Final segmentation result. ........................................... 159
5.24 Texture image segmentation with representative pixels identified automatically. (a) Input texture image, which is shown in Figure 5.12. (b) Initial classification result. Here the representative pixels are detected automatically. (c) Final segmentation result.

5.25 Texture image segmentation with representative pixels identified automatically. \( W(s) \) is a \( 29 \times 29 \) square window, \( W(a) \) is a \( 43 \times 43 \) square window, \( \lambda_C = 0.1 \), \( \lambda_A = 0.2 \), \( \lambda_B = 5.0 \), \( \lambda_T = 0.4 \), and \( T_A = 0.20 \). (a) Input texture image, which is shown in Figure 5.13. Here the representative pixels are detected automatically. (c) Final segmentation result.

5.26 (a) A texture image with size \( 256 \times 256 \). (b) The segmentation result using spectral histograms. (c) Wrongly segmented pixels of (b), represented in black with respect to the ground truth. The segmentation error is 6.55%. (d) Refined segmentation result. (e) Wrongly segmentation pixels of (d), represented in black as in (c). The segmentation error is 0.95%.

5.27 (a) A synthetic image with size \( 128 \times 128 \), as shown in Figure 5.7(a). (b) The segmentation result using spectral histograms as shown in Figure 5.7(c). (c) Refined segmentation result.

5.28 (a) A texture image with size \( 256 \times 256 \). (b) The segmentation result using spectral histograms. (c) Refined segmentation result.

5.29 (a) A texture image with size \( 256 \times 256 \). (b) The segmentation result using spectral histograms. (c) Refined segmentation result.

5.30 Distance between scales for different regions. (a) Input image. (b) The distance between different integration scales for the left region at pixel \( (32, 64) \). (c) The distance between different integration scales for the right region at pixel \( (96, 64) \).

5.31 A natural image with a zebra. \( \lambda_T = 0.2 \), and \( \lambda_B = 5.5 \). (a) The input image. (b) The segmentation result with one feature computed at \( (205, 279) \). (c) The segmentation result with one feature computed at \( (308, 298) \). (d) The combined result from (b) and (c).
6.1 On- and off-center cell responses. (a) Input image. (b) On-center cell responses. (c) Off-center cell responses (d) Binarized on- and off-center cell responses. White regions represent on-center response regions and black off-center regions.

6.2 The figure-ground segregation network architecture for Figure 6.1(a). Nodes 1, 2, 3 and 4 belong to the white region; Nodes 5, 6, 7, and 8 belong to the black region; Nodes 9 and 10, 11 and 12 belong to the left and right gray regions respectively. Solid lines represent excitatory coupling while dashed lines represent inhibitory connections.

6.3 Temporal behavior of each node in the network shown in Figure 6.2. Each plot shows the status of the node with respect to the time. The dashed line is 0.5.

6.4 Surface completion results for Figure 6.1(a). (a) White region. (b) Gray region. (c) Black region.

6.5 Layered representation of surface completion for results shown in Figure 6.4.

6.6 Images with virtual contours. (a) Kanizsa triangle. (b) Woven square. (c) Double kanizsa.

6.7 Surface completion results for the corresponding image in Figure 6.6.

6.8 Images with virtual contours. (a) Kanizsa triangle. (b) Four crosses. (c) Overlapping rectangular bars.

6.9 Surface completion results for the corresponding image in Figure 6.8.

6.10 Images with virtual contours. (a) Original pacman image. (b) Mixed pacman image. (c) Alternate pacman image.

6.11 Layered representation of surface completion for the corresponding images shown in Figure 6.10.

6.12 Bregman and real images. (a) and (b) Examples by Bregman [9]. (c) A grocery store image.

6.13 Surface completion results for images shown in Figure 6.12.
6.14 Bistable perception. (a) Face-vase input image. (b) Faces as figures. (c) Vase as figure.

6.15 Temporal behavior of the system for Figure 6.14(a). Dotted lines are 0.5.

7.1 Classification result of a noisy synthetic image using a three-layer perceptron. (a) The input image with size of $230 \times 240$. (b) The ground truth image. (c) Positive and negative training samples. Positive examples are shown as white and negative ones as black. (d) Classification result from a three-layer perceptron.

7.2 Lateral connection evolution through weight adaptation illustrated using the 170th row from the image shown in Figure 7.1(a). (a) The original signal. (b) Initial connection weights. (c) Connection weights after 40 iterations. (d) Corresponding smoothed signal.

7.3 Architecture and local features for the seed selection neural network.

7.4 Segmentation result using the proposed method for a synthetic image. (a) A synthetic image as shown in Figure 7.1(a). (b) The segmentation result from the proposed method. Here $W_z = 0.25$ and $\theta_p = 100$.

7.5 A DOQQ image with size of $6204 \times 7676$ pixels of the Washington East, D.C.-Maryland area.

7.6 Seed pixels obtained by applying a trained three-layer perceptron to the DOQQ image shown in Figure 7.5. Seed pixels are marked as white and superimposed on the original image. The network is trained using 19 positive and 28 negative samples, where each sample is a $31 \times 31$ window.

7.7 Extracted hydrographic regions from the DOQQ image shown in Figure 7.5. Hydrographic regions are marked as white and superimposed on the original image to show the accuracy of the extracted result. Here $W_z = 0.15$ and $\theta_p = 4000$.

7.8 A ground truth generated by manually placing seeds based on the corresponding 1:24,000 USGS topographic map and DOQQ image. The result was manually edited.
7.9 Hydrographic region extraction result for an aquatic garden area with manually placed seed pixels. Due that no reliable seed region is detected, this aquatic region, which is very similar to soil regions, is not extracted from the DOQQ image as shown in Figure 7.7. Extracted regions are marked as white and superimposed on the original image.

7.10 Extraction result for an image patch from Figure 7.5. (a) The input image. (b) The seed points from the neural network. (c) A topographic map of the area. Here the map is scanned from the chapter version and not wrapped with respect to the image. (d) Extracted result from the proposed method. Extracted regions are represented by white and superimposed on the original image.

7.11 A DOQQ image with size of $5802 \times 7560$ pixels of Damascus, Pennsylvania-New York area.

7.12 Extracted hydrographic regions from the DOQQ image shown in Figure 7.11. The extracted regions are represented by white pixels and superimposed on the original image.

7.13 A ground truth generated based on a 1:24,000 USGS topographic map and DOQQ image.

8.1 A stereo image pair and correspondence using the spectral histogram. (a) The left image. (b) The right image. (c)-(e) The matching results of marked pixels in the left image. In each row, the left shows the marked pixel, the middle shows the probability of being a match in the paired image, and the right shows the high probability area in the paired image.

8.2 Comparison between en edge detector and the spectral histogram using a natural image of a giraffe. (a) The input image with size $300 \times 240$. (b) The edge map from a Canny edge detector [13]. (c) The initial classification result using the method presented in Chapter 5. A spectral histogram is extracted at pixel $(209, 291)$ and the segmentation scale is $29 \times 29$. (d) The initial classification is embedded in the input image to show the boundaries.