5. Foreground Objects Detection & Background Separation

5.1 Introduction

The chapter covers a novel method of background separation, revealing foreground objects for color images. The approach effectively incorporates visually prominent boundaries, prominence measure of pixels and local color & region cues along with Watershed transform. The proposed method addresses the issues for avoiding under segmentation and over segmentation by enforced reliable processing of local cues used for producing continuity preserving prominent boundaries. The method results, incorporating different levels of stationary Haar wavelet decompositions are compared, analyzed and presented. The effectiveness, suitability and versatility of the method for well localization of prominent boundaries leading to foreground extraction are shown by qualitative comparisons of method results with that of human segmented images of benchmark-image-dataset [Fowlkes, on line] [Martin, 2001]. In the last portion of the chapter, segmentation results of JSEG [Deng, on line] [Deng, 2001] are qualitatively compared with the results of proposed method for observing effects of illumination changes and texture variations.

The reliable and precise processing of low level cues in pixel domain is very important and crucial for over all performance of any image processing applications handing out image features derived or inferred from these low level cues. The precise and reliable processing of low level cues for feature extraction is tested by various factors like image resolutions, intra-image illumination variations, non-homogeneity of intra-region and inter-region textures, multiple and occluded objects etc. The foreground objects revealing by separating the background is, in general, a subsequent phase of image segmentation. Image segmentation is a process of identifying and then grouping region-forming pixels, satisfying single or multiple constraints. The diversities of image characteristics enforce requirements of parameter selection and / or parameter tuning or user interaction for better performance of generic segmentation algorithms. The performance of the segmentation algorithm is hence evaluated with Precision-Recall measures for different segmentation scales. So, for a given scale, any segmentation algorithm faces the biggest challenge of avoiding over and under segmentations – subjective and image category dependent criterions. Thus, the subjectivity in the human perception for segmentation, required scale of segmentation and diversified image characteristics play decisive role for justifying proper segmentation of the images. The foreground objects detection is severely affected by a lapse generated during segmentation phase.

Similarly, difficulties do exist with watershed algorithms. The watershed algorithms find catchments basins by locating local minima, resulting into artifacts and over segmentation. The conversion of color image into gray scale image produces local minima leading to artifacts and conversion of gray scale image into binary introduces breaks likely to cause under segmentations. As illustrated in top-right of Figure 33, the watershed regions of gray scale converted image are large in numbers and small in sizes, producing over segmented image. Similarly, the watershed regions obtained from dithered image exhibits relatively lesser number of segments due to lossy conversion, giving still few over segmented zones in the image, as shown in bottom-right of Figure 33. Thus, for distinction of objects using resulted watershed regions, additional low level cues must be incorporated for selective merging of these regions. Hence, marking of well localized object boundaries becomes the necessary condition for proper object detection.

The proposed approach is based on precisely detected prominent boundaries with continuity preservation for minimizing chances of them being leaky. The problem of foreground objects revealing of prominent boundaries detected images has been addressed in the hierarchical frame work incorporating wavelet decomposed images at various levels along with proximity influence measure and watershed transform.

5.2 The Method

The method exploits stationary Haar wavelet for decomposing RGB images at various levels. The well localized, visually prominent, continuous boundaries encompassing various regions called prominent boundaries are detected as proposed in Algorithm 2, Section 4.4.1. The prominent boundaries are categorized candidate boundaries. The non-prominent boundaries resulted because of smooth variations in textures and colors are excluded because of the categorization. The proposed method is novel for its prominent boundary features, proximity influence measures and its usage for watershed regions. Many variational techniques to reduce watershed artifacts were tried out for development of proposed method. The watershed transform of Matlab R14, a modification of basic watershed algorithm of [Vincent, 1991] has been utilized in following algorithm with 8 neighbor connectivity.

The steps of the proposed method are:

Step 1: Detect prominent boundaries by applying proposed method of Algorithm 2, Section 4.4.1.

Denote the set of prominent contours as $P_c = \{Vi\}$, $i > 0$, where Vi is a vector, corresponding to i^{th} contour of color channel c consisting of coordinate-pairs denoted as $\{(x_j, y_j)\}$, $j > 0$.

Apply operator χ to map P_c on the image I(x, y z) to get prominent-boundaries-mapped image, given as

$I'(x, y, z) = P_c \chi I (x, y, z)$ such that

$I'(x, y, z) = I (x, y, z)$, if $x, y \in P_c$

and $I'(x, y, :) = \{255,255,255\}$, otherwise.

Step 2: For all pixels on prominent boundaries, compute total proximity influence value i.e. prominence measure induced by vertices of prominent contours of channel under considerations on nearest neighboring prominent pixels. Refer Section 4.1.1 for prominence measure computation. Denote it as $UP_c(x, y)$. At the given point, higher the value stronger is the boundary strength. Refer Figure 31 (c) for the results.

Step 3: Perform watershed transformation on $UP_c(x, y)$. Refer Figure 31 (d) for the results.

Step 4: Perform morphological operation on $UP_c(x, y)$ to get $UP'_c(x, y)$. Refer Figure 31 (e) for the results.

Step 5: Perform watershed transformation on $UP'_c(x, y)$.

Label watershed region. Refer Figure 31 (f) for the results.

Step 6: Repeat previous steps for all channels.

Step 7: Find composite prominence measure UP'' and watershed transform. Label watershed regions. Refer Figure 32 (a) for the results.

Composite prominence measure is total of prominence measure of all 4 channels.

Step 8: Let SP = {(x_i, y_i)} such that $x_i, y_i \notin P_c$, a fixed set of seed points determined empirically.

$BG(x, y) = ((I'(x, y, z), UP''(x, y)) \upsilon SP) \varsigma I(x, y, z)$.

Where,

υ - Denotes morphological operations involving region growing algorithm based image filling implementation of Matlab R14.

ς - Denotes mapping operator to extract the background.

And, find foreground *as*

$FG(x, y) = I(x, y) \sim BG(x, y)$.

Where,

$\sim$ - Denotes exclusion operator to reveal the foreground from the original image by excluding the background.

Refer Figure 32 (b) for the results.

Step 9: Find watershed pixels constituting foreground object boundaries. The watershed pixels are the pixels not belonging to any regions. Two rows and two columns on the image boundaries are excluded.

Refer Figure 32 (c) for the results.

Step 10: Find the region attributes of foreground objects.

Algorithm 3. Foreground objects detection & background separation.

5.3 Results

The intermediate results produced by the method, qualitative comparison of results on typical representative images including images of standards databases and qualitative comparison of results of proposed method with that of JSEG [Deng, on line] [Deng, 2001] and human segmented images of standard databases [Fowlkes, on line] [Martin, 2001]are presented in this section.

5.3.1 Step-wise Results of the Method

The original image [Everingham, on line] and detected prominent boundaries of all four channels are shown in Figure 31 (a) and Figure 31 (b) respectively. Figure 31 (c) shows the results of prominence measure for prominent boundaries of each channel. Figure 31 (d) is the results of labeled watershed transform regions corresponding to Figure 31 (c). Though prominent boundaries were detected precisely, the generated watershed regions do not depict all regions of foreground. The morphological operations are performed to get enhanced prominence measures as shown in Figure 31 (e).

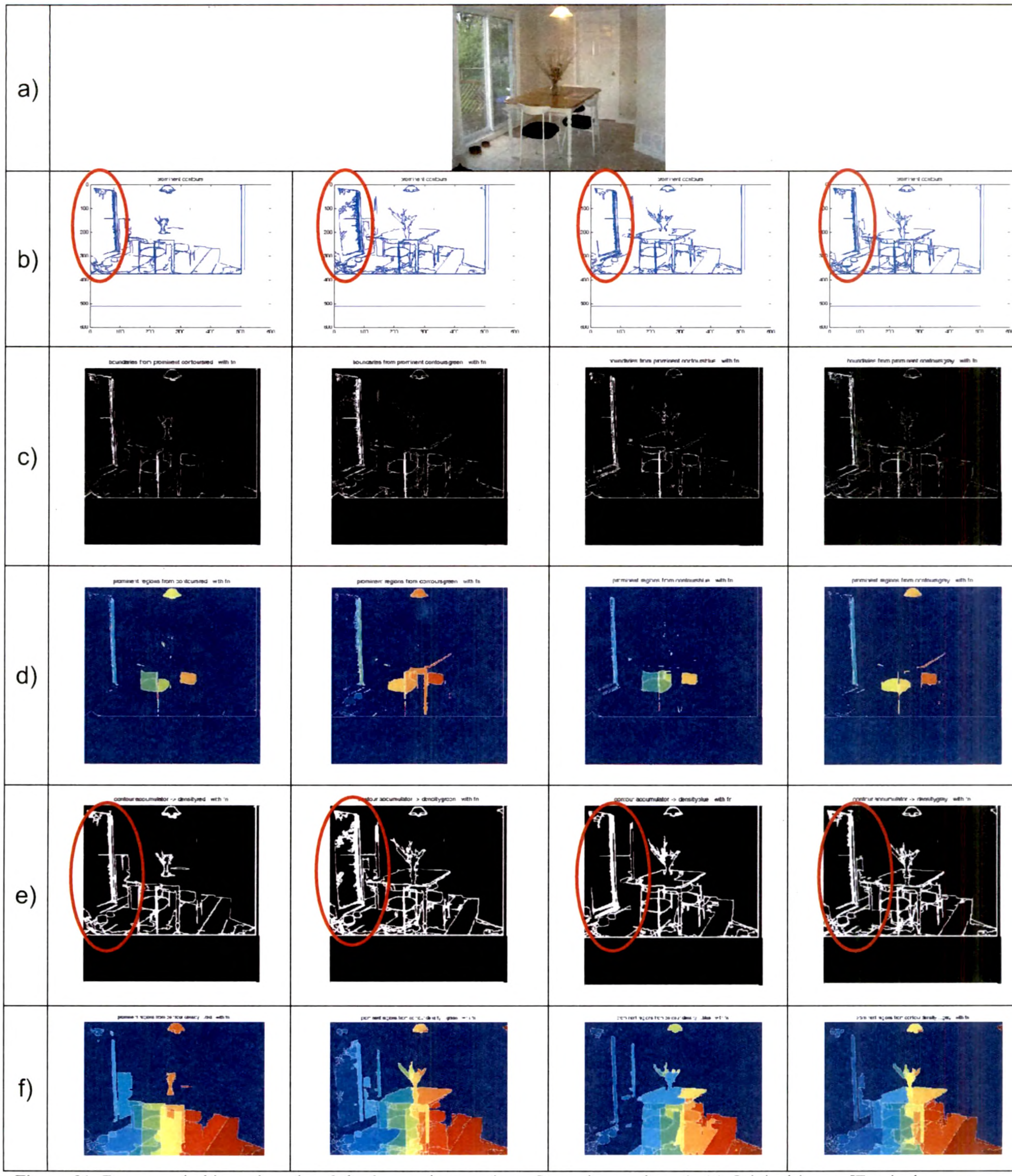


Figure 31. Foreground objects detection & background separation - Step-wise results – 1. (a) Original image [Everingham, on line]. (b) Prominent boundaries of R, G, B and Gray channels.(c) Respective prominence measures. (d) Respective labeled watershed regions of (c). (e) Respective enhanced prominence measures after morphological operations. (f) Respective labeled watershed regions of (e).

As the contribution of each channel for defining real prominent boundaries is non-homogeneous, individual prominent boundaries and corresponding prominence measures of each channel still do not cover all real prominent boundaries, as illustrated by encircling such portion of boundaries in Figure 31 (e). The labeled watershed regions corresponding to Figure 31 (e) are shown in Figure 31 (f).

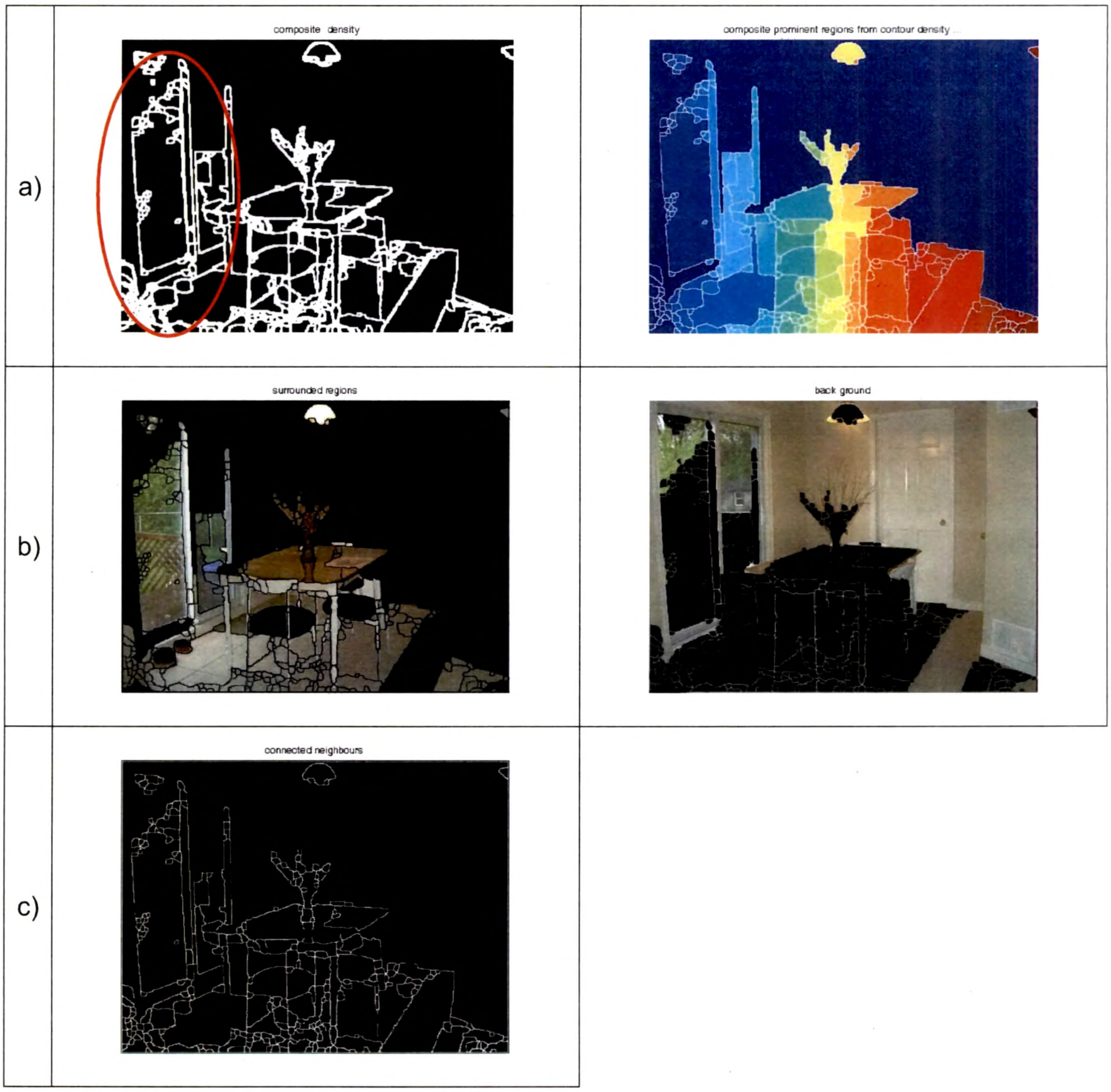


Figure 32. Foreground objects detection & background separation - Step-wise results – 2. (a) Left – Composite watershed regions from Figure 31 (e). (a) Right – Labeled watershed regions. (b) Left - Extracted foreground. (b) Right – background. (c) Watershed pixels of foreground regions.

The composite prominence measure obtained is shown in Figure 32 (a) - Left and respective labeled watershed regions are presented in Figure 32 (a) Right. The extracted foreground and background are shown in Figure 32 (b) – Left and Figure 32 (b) – Right respectively. The watershed pixels corresponding to foreground and foreground regions are shown in Figure 32 (c).

5.3.2 Qualitative Comparisons

Table 4. Categorical Representative Test Images & Their Performance Challenging Salient Characteristics.

Figure 34	A natural image [Wang, 2001] [SIMPLIcity, on line]; textured background; foreground object having intra-object texture variations.
Figure 35, Left	A typical image [Wang, 2001] [SIMPLIcity, on line] of a human face; textured background;
Figure 35, Right	A synthesized image [Wang, 2001] [SIMPLIcity, on line]; a single central main foreground object with a typical texture; homogeneous background;
Figure 36, Left	An image resized to 1/8th of the original size; image captured by an amateur with high resolution SONY device having inbuilt bionz image processor.
Figure 36, Right	A natural image [Wang, 2001] [SIMPLIcity, on line]; multiple-textured background; foreground object having intra-object texture variations; shadowed foreground object.
Figure 37, Left	A natural image [Wang, 2001] [SIMPLIcity, on line]; multiple similar partially touching foreground objects.
Figure 37, Right	An image [University of Washington, on line] with multiple textures; self reflection attached to foreground object;
Figures 38 - 41	The BSDB test images & associated human segmented images [Fowlkes, on line] [Martin, 2001]; covering multiple objects, occluded and shadowed objects, natural and man-made objects; distant and small objects; inter region and intra-region texture variations in foreground objects and background;

The image segmentation by human being is intrinsically characterized by grouping of regions based on 'some' perceptual similarities. Though there exists subjectivity in the perception of visual similarities, human beings do not over-segment the objects contained in the images. That is, the focus of segmentation by humans is objects and not regions. Hence, the results of proposed method for foreground detection have been qualitatively compared with the human segmented images of Berkeley Segmentation Dataset and Benchmark database of natural images [Fowlkes, on line] [Martin, 2001].

The results on categorical representative test images, possessing performance challenging salient characteristics listed in Table 4, are shown in Figure 34 to Figure 41. The results presented are for prominent boundaries detection, separation of background, revealing of foreground objects, region features using watershed transform and corresponding watershed pixels of foreground objects and artifacts reduced regions and corresponding boundaries by incorporating different levels of stationary Haar wavelet decomposition. Figure 34 demonstrates results with different levels of SWT on an image [Wang, 2001] [SIMPLIcity, on line] having texture variations in the foreground object as well as in the background. The detected prominent boundaries incorporating SWT with Haar wavelet at level 1, 2 and 3 are shown in Figure 34 (b) from left to right respectively. The corresponding separated background is shown in Figure 34 (c), where pure black regions do not belong to the background. The corresponding foreground is shown in Figure 34 (d), where pure black regions do not belong to the foreground. The watershed regions and watershed pixels are respectively shown in Figure 34 (e) and Figure 34 (f). The watershed regions and watershed pixels with reduced artifacts are respectively shown in Figure 34 (g) and Figure 34 (h). Figure 35 - Left shows the results on the image [Wang, 2001] [SIMPLIcity, on line] having poorly defined object boundaries where the Haar stationary wavelet decompositions of step 1 of the method are omitted. Figure 35-Right to Figure 37 demonstrates the results incorporating Haar wavelet decompositions at level 2 on different categorical representative test images. Figure 38 and Figure 39 show comparison of the method results with stationary Haar wavelet decompositions at level 2 and level 3 on images [Fowlkes, on line] [Martin, 2001] with human segmented images of Segmentation Dataset and Benchmark [Fowlkes, on line] [Martin, 2001]. Similarly, Figure 40 and Figure 41 show comparison of the method results with stationary Haar wavelet decompositions at level 2 on different categorical representative test images [Fowlkes, on line] [Martin, 2001] with human segmented images of segmentation dataset and benchmark [Fowlkes, on line] [Martin, 2001].

The results are to be observed and compared for

- Localization of detected boundaries.
- Effect of complex background, textures on segmentation / foreground extraction.
- Effect on segmentation / foreground extraction due to smooth changes.
  - in textured regions
  - of colors within regions
  - of intensities within region
- Suitability of segmentation results for foreground separation / object detection.
- Human segmented images of BSDB [Fowlkes, on line] [Martin, 2001].

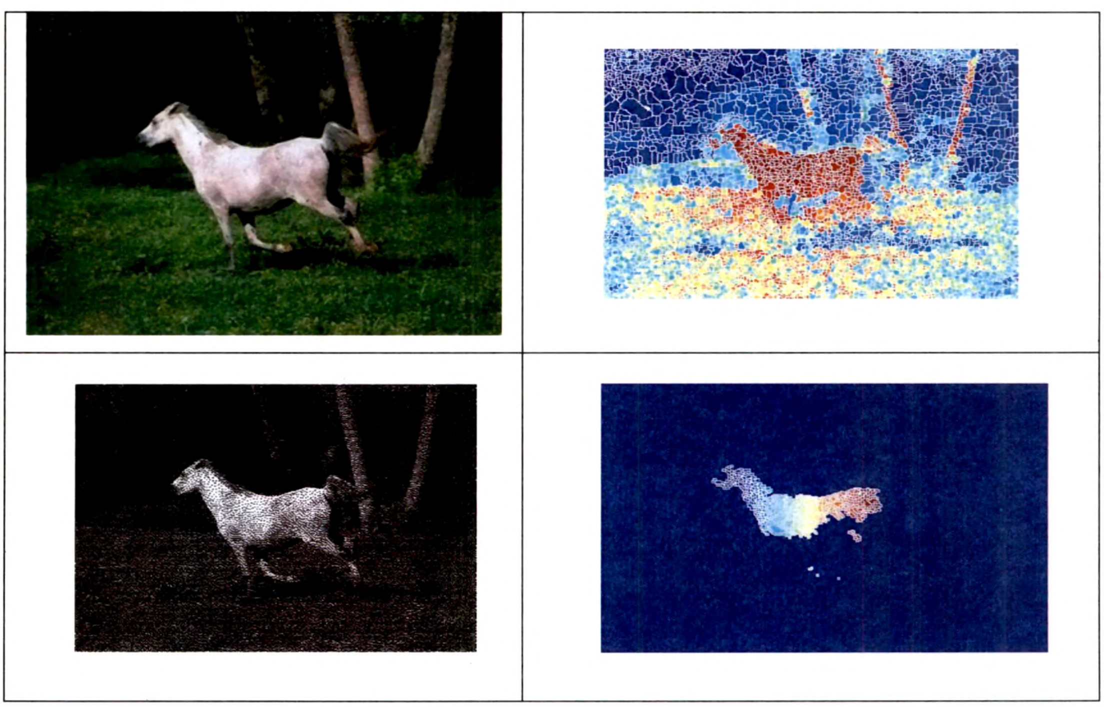


Figure 33. Watershed transform based segmentation without applying proposed method. Top-left: Original image [Wang, 2001] [SIMPLIcity, on line]. Top-right: Watershed regions of gray scale converted image of top-left. Bottom-left: Dithered image of top-left. Bottom –right: Watershed regions of dithered image.

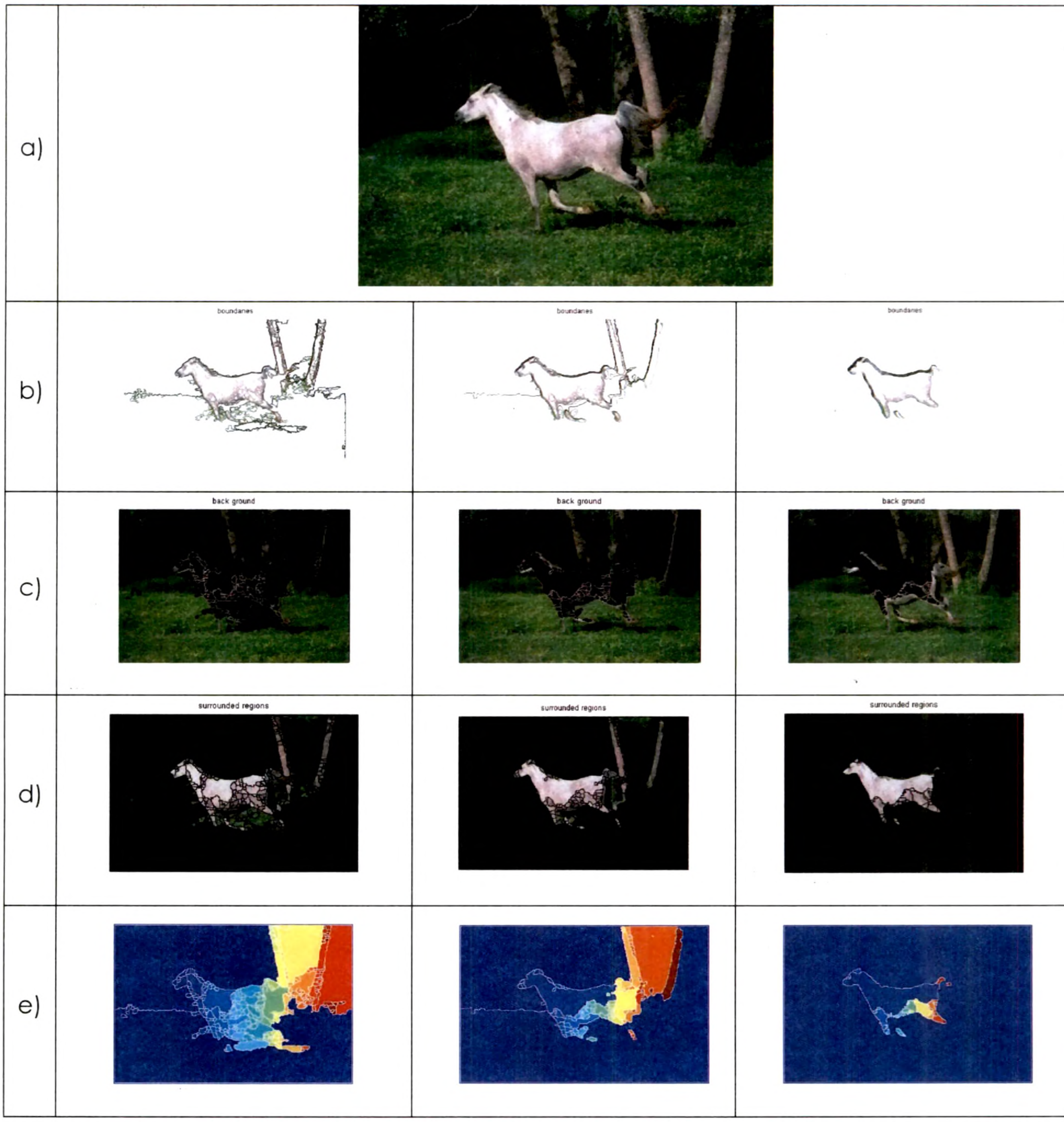


Figure 34. Revealed fore ground objects & background, incorporating different levels of wavelet decompositions. (a) Original image [Wang, 2001] [SIMPLIcity, on line]. (b) Detected prominent boundaries. Left: Incorporating stationary Haar wavelet decomposition at level 1. Middle: Incorporating stationary Haar wavelet decomposition at level 2. Right: Incorporating stationary Haar wavelet decomposition at level 3. (c) Separated background. (d) Revealed foreground. (e) Watershed regions.

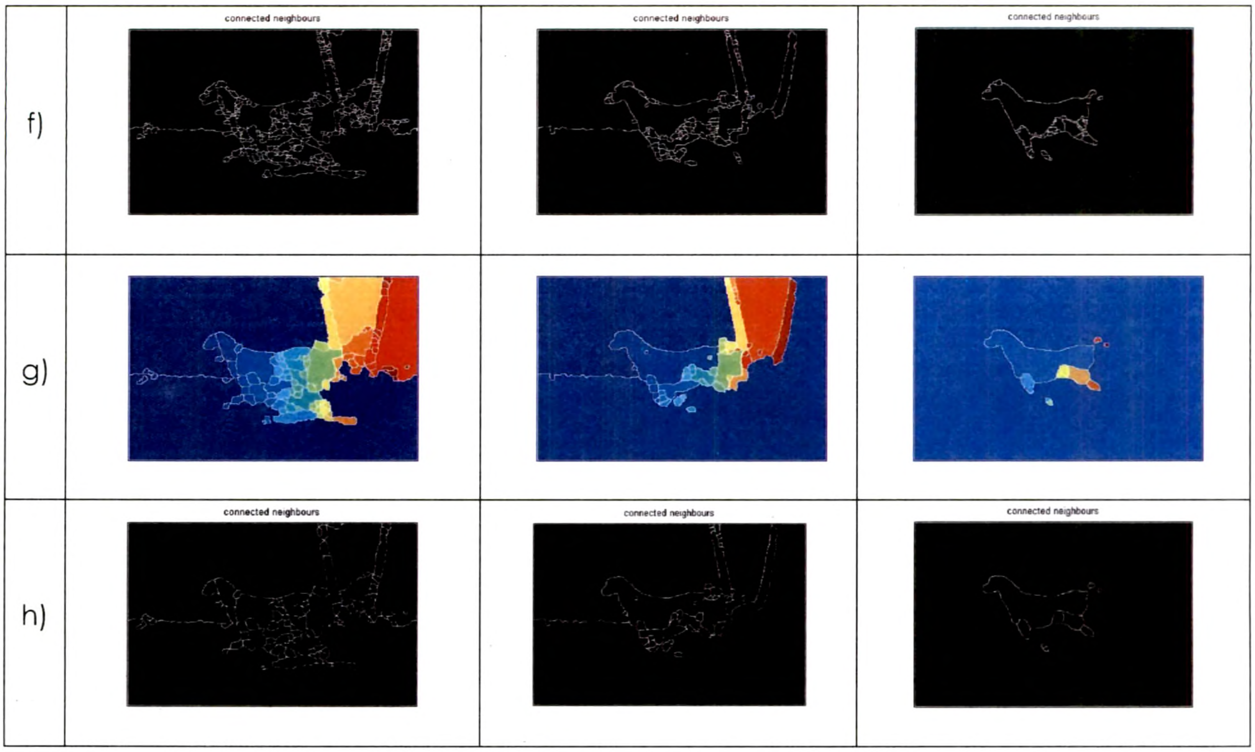


Figure 34. (Contd.). Revealed fore ground objects & background, incorporating different levels of wavelet decompositions. (f) Corresponding watershed pixels of foreground object boundaries. (g) Watershed regions with reduced artifacts. (h) Corresponding watershed pixels of foreground object boundaries.

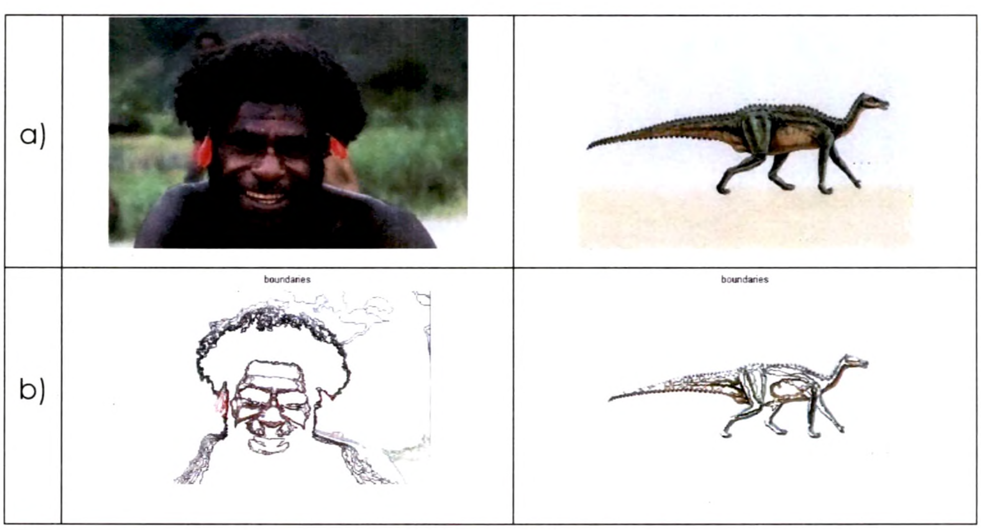


Figure 35. Revealed fore ground objects & background for images with typical textures. (a) Original images [Wang, 2001] [SIMPLIcity, on line]. (b) Detected prominent boundaries. Left: Without wavelet decomposition. Right: Incorporating stationary Haar wavelet decomposition at level 2.

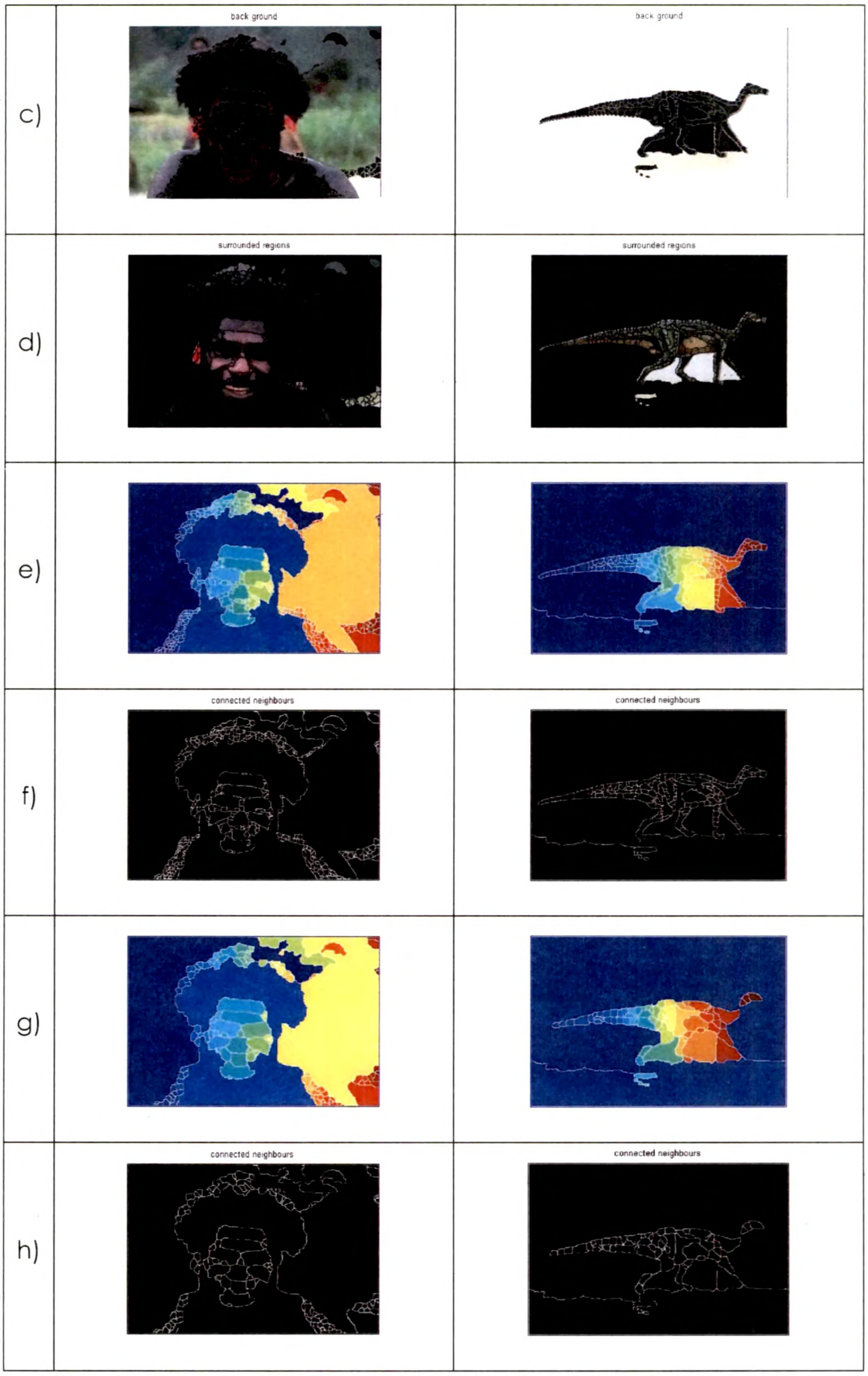


Figure 35 (Contd.). Revealed fore ground objects & background for images with typical textures. (c) Separated background. (d) Revealed foreground. (e) Watershed regions. (f) Corresponding watershed pixels of foreground object boundaries. (g) Watershed regions with reduced artifacts. (h) Corresponding watershed pixels of foreground object boundaries.

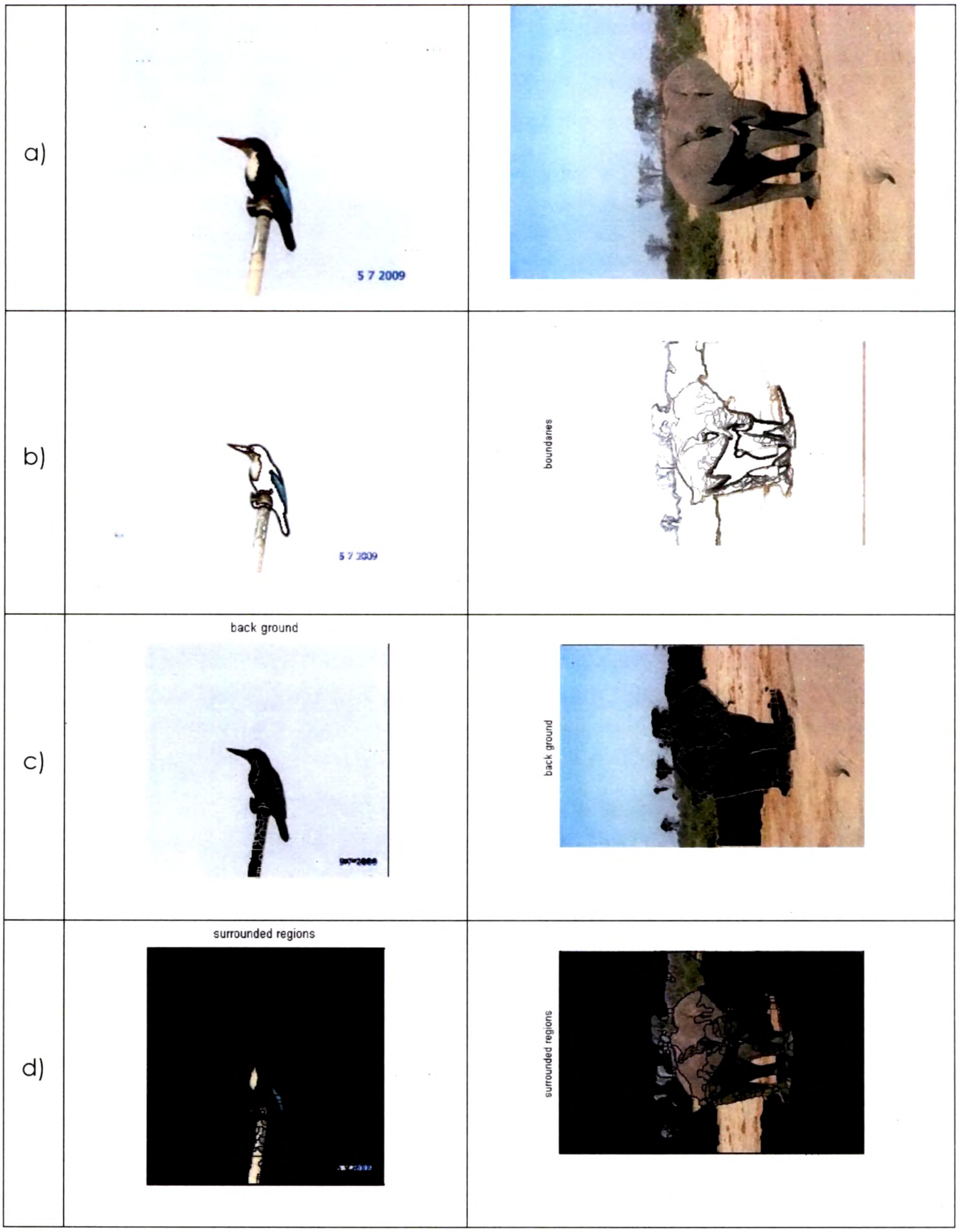


Figure 36. Revealed foreground objects & background, incorporating stationary Haar wavelet decompositions at level 2. (a) Left: Original image. Right: Original image [Wang, 2001] [SIMPLIcity, on line]. (b) Detected prominent boundaries. (c) Separated background. (d) Revealed foreground.

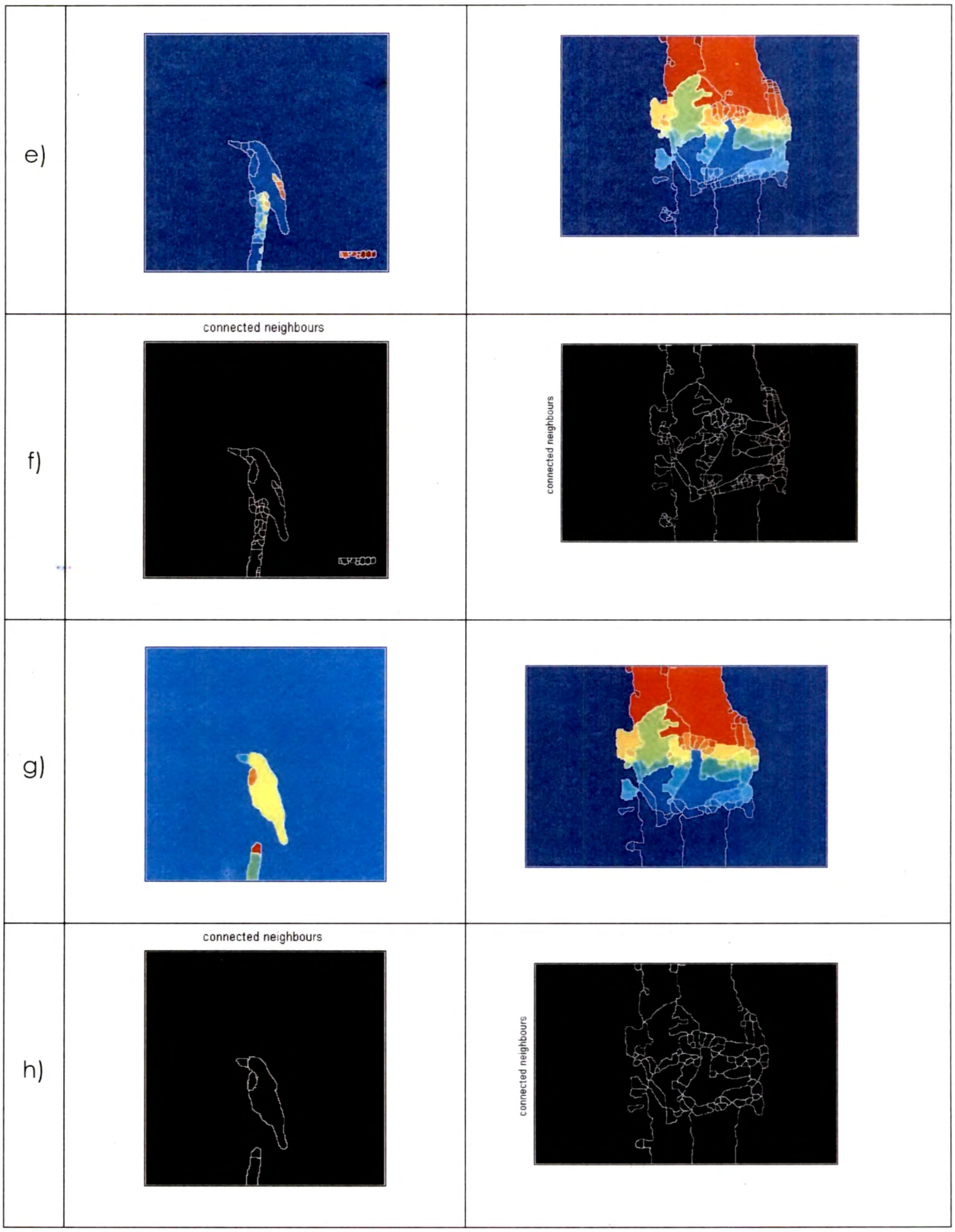


Figure 36. (Contd.). Revealed foreground objects & background, incorporating stationary Haar wavelet decompositions at level 2. (e) Watershed regions. (f) Corresponding watershed pixels of foreground object boundaries. (g) Watershed regions with reduced artifacts. (h) Corresponding watershed pixels of foreground object boundaries.

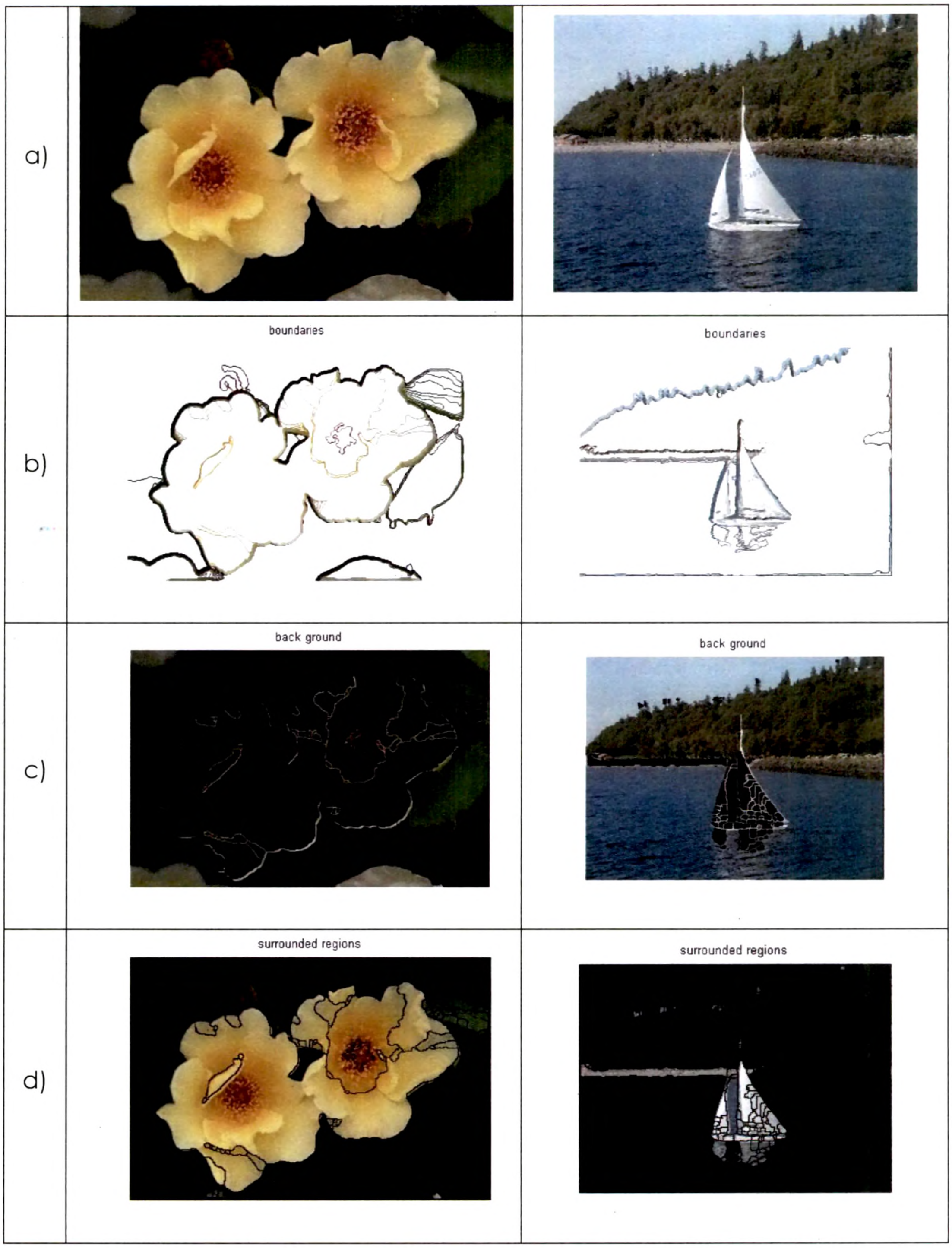


Figure 37. Revealed foreground objects & background, incorporating stationary Haar wavelet decompositions at level 2. (a) Left: Original Image [Wang, 2001] [SIMPLIcity, on line]. Right: Original image [University of Washington, on line]. (b) Detected prominent boundaries. (c) Separated background. (d) Revealed foreground.

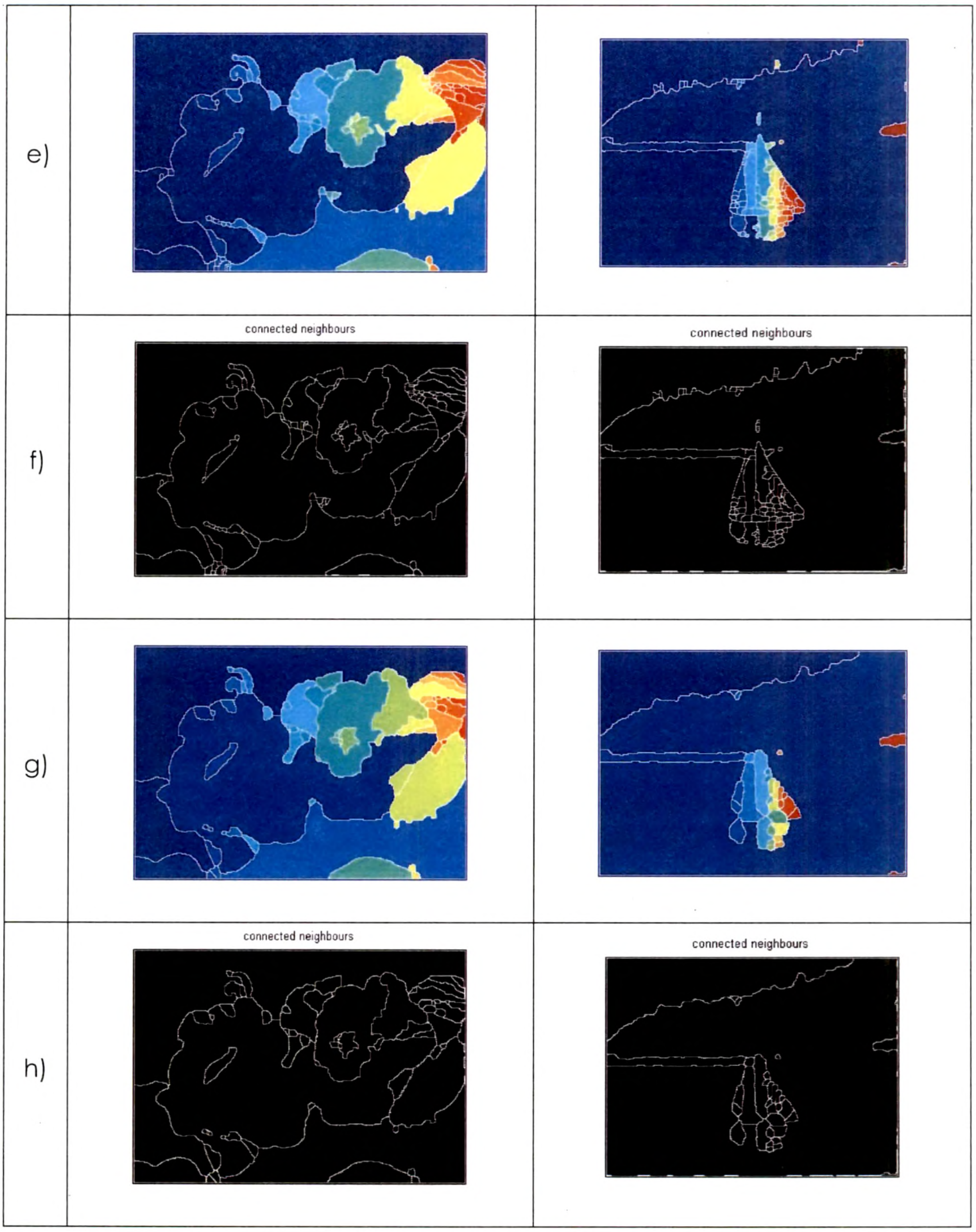


Figure 37 (Contd.). Revealed foreground objects & background, incorporating stationary Haar wavelet decompositions at level 2. (e) Watershed regions. (f) Corresponding watershed pixels of foreground object boundaries. (g) Watershed regions with reduced artifacts. (h) Corresponding watershed pixels of foreground object boundaries.

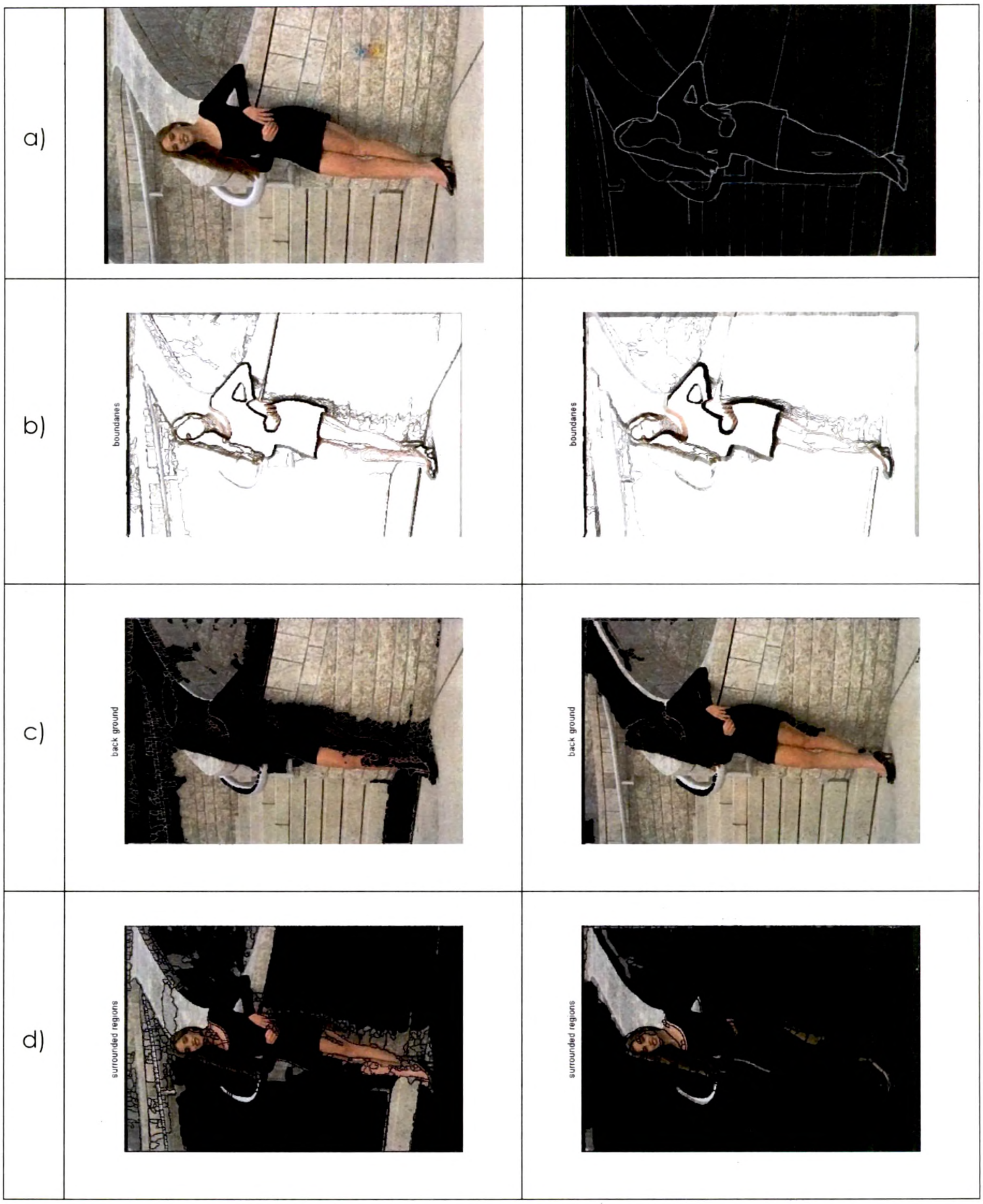


Figure 38. Result-comparison: Human segmented image with revealed foreground objects & background, incorporating different levels of stationary Haar wavelet decompositions. (a) Left: Original image [Fowlkes, on line] [Martin, 2001]. Right: Human segmented image [Fowlkes, on line] [Martin, 2001]. (b) Detected prominent boundaries. Left: Incorporating stationary Haar wavelet decomposition at level 2. Right: Incorporating stationary Haar wavelet decomposition at level 3. (c) Separated background. (d) Revealed foreground.

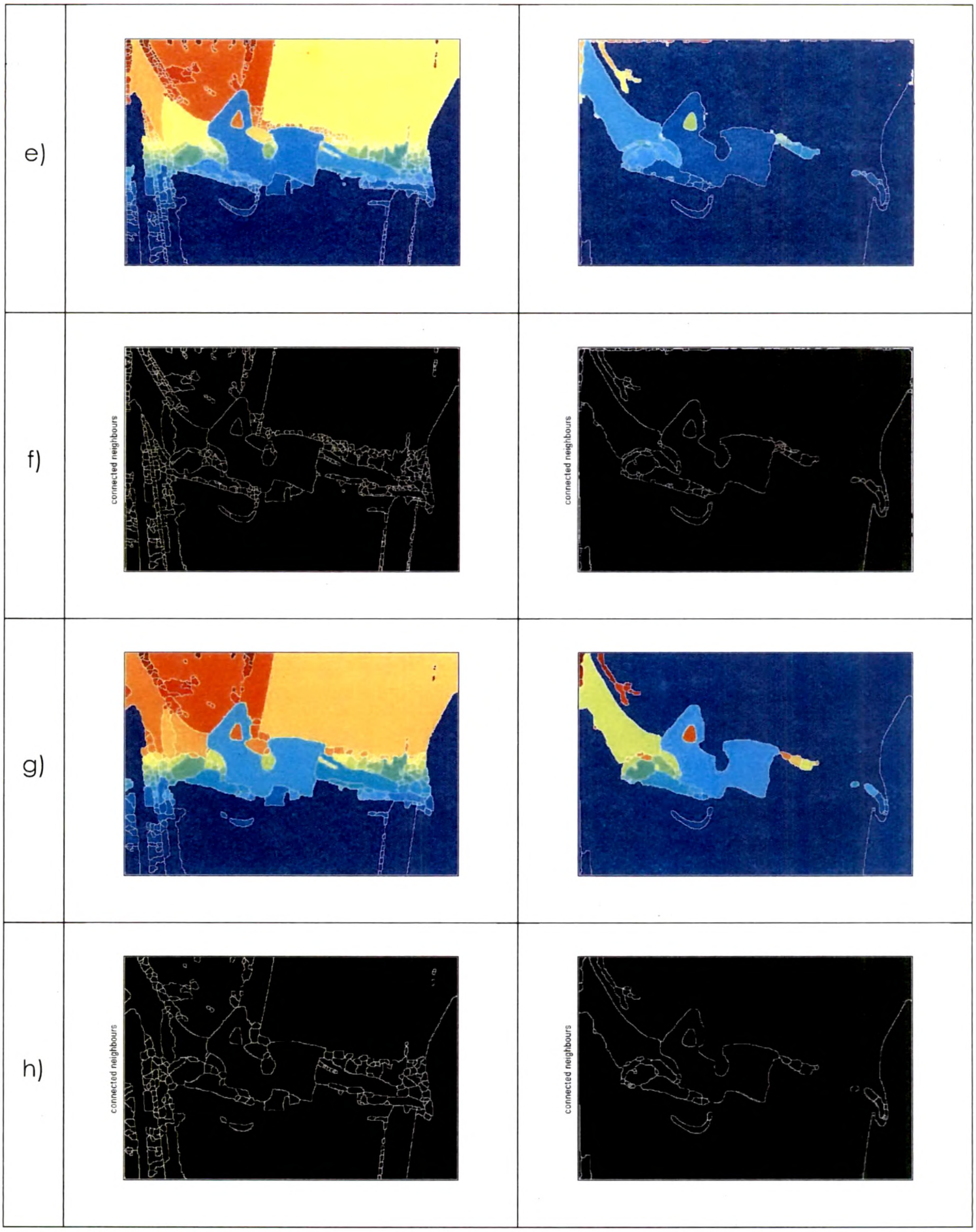


Figure 38 (Contd.). Result-comparison: Human segmented image with revealed foreground objects & background, incorporating different levels of stationary Haar wavelet decompositions. (e) Watershed regions. (f) Corresponding watershed pixels of foreground object boundaries. (g) Watershed regions with reduced artifacts. (h) Corresponding watershed pixels of foreground object boundaries.

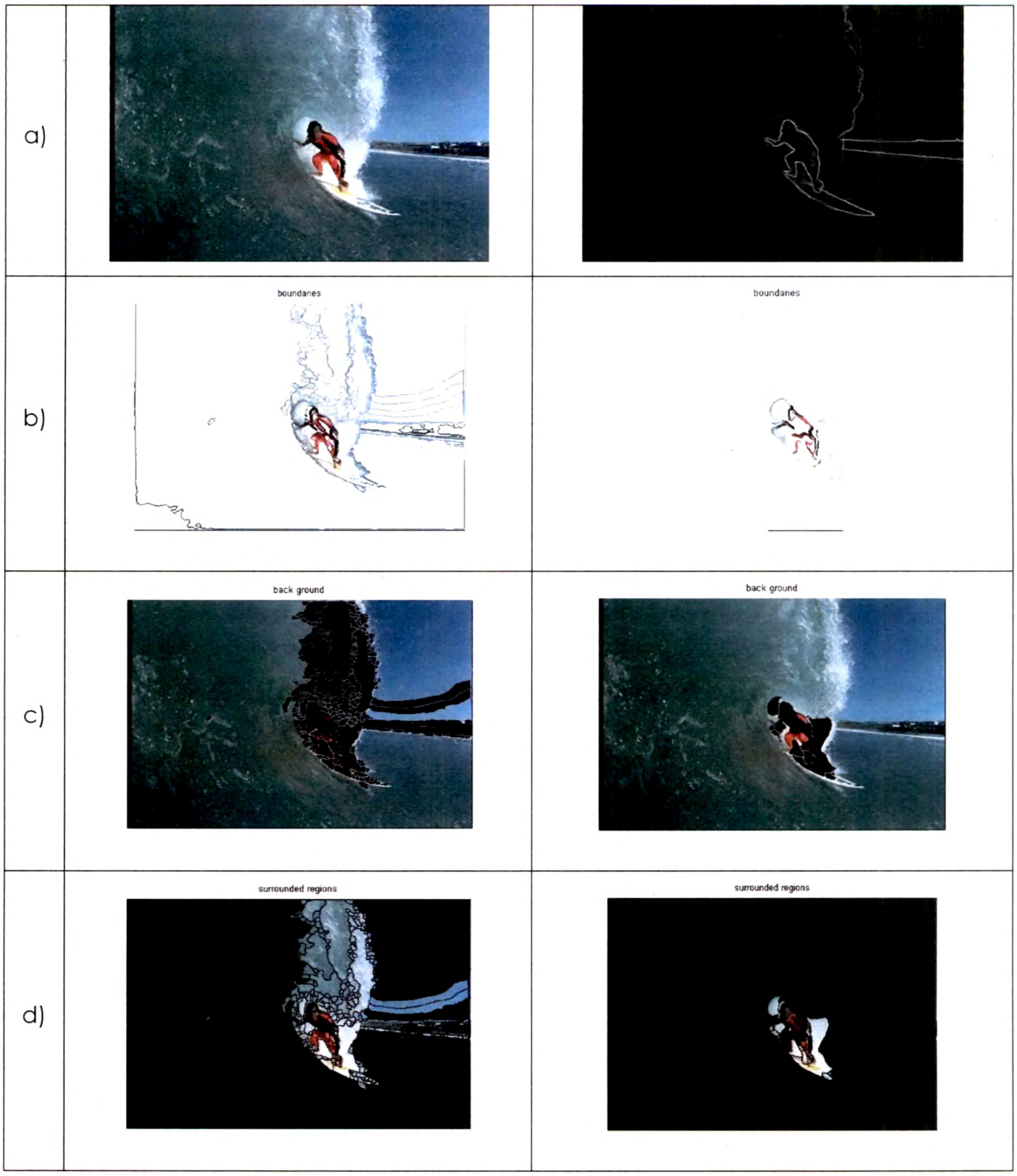
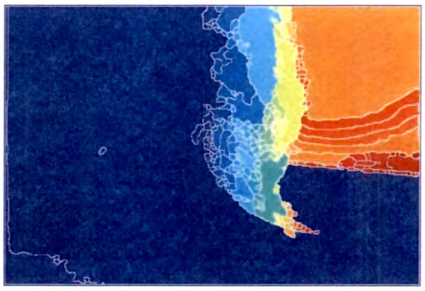
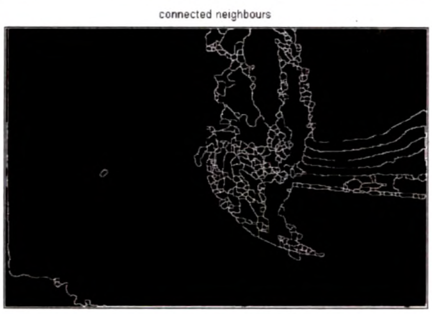


Figure 39. Result-comparison: Human segmented image with revealed foreground objects & background, incorporating different levels of stationary Haar wavelet decompositions. (a) Left: Original image [Fowlkes, on line] [Martin, 2001]. Right: Human segmented image [Fowlkes, on line] [Martin, 2001]. (b) Detected prominent boundaries. Left: Incorporating stationary Haar wavelet decomposition at level 2. Right: Incorporating stationary Haar wavelet decomposition at level 3. (c) Separated background. (d) Revealed foreground.

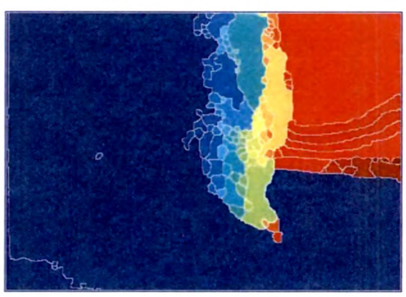
e)

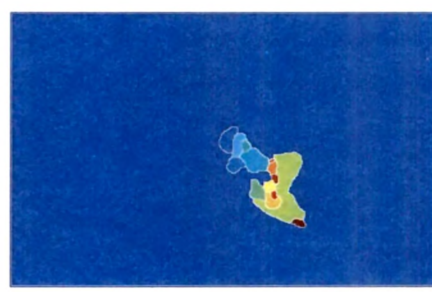


f)

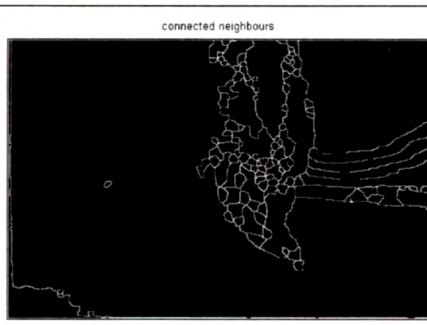


g)





h)



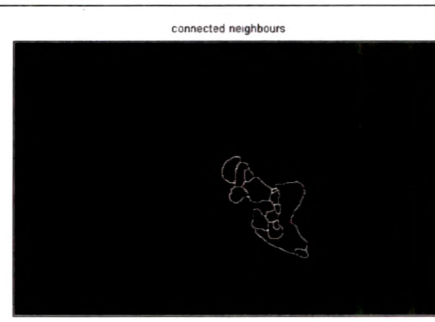


Figure 39 (Contd.). Result-comparison: Human segmented image with revealed foreground objects & background, incorporating different levels of stationary Haar wavelet decompositions. (e) Watershed regions. (f) Corresponding watershed pixels of foreground object boundaries. (g) Watershed regions with reduced artifacts. (h) Corresponding watershed pixels of foreground object boundaries.

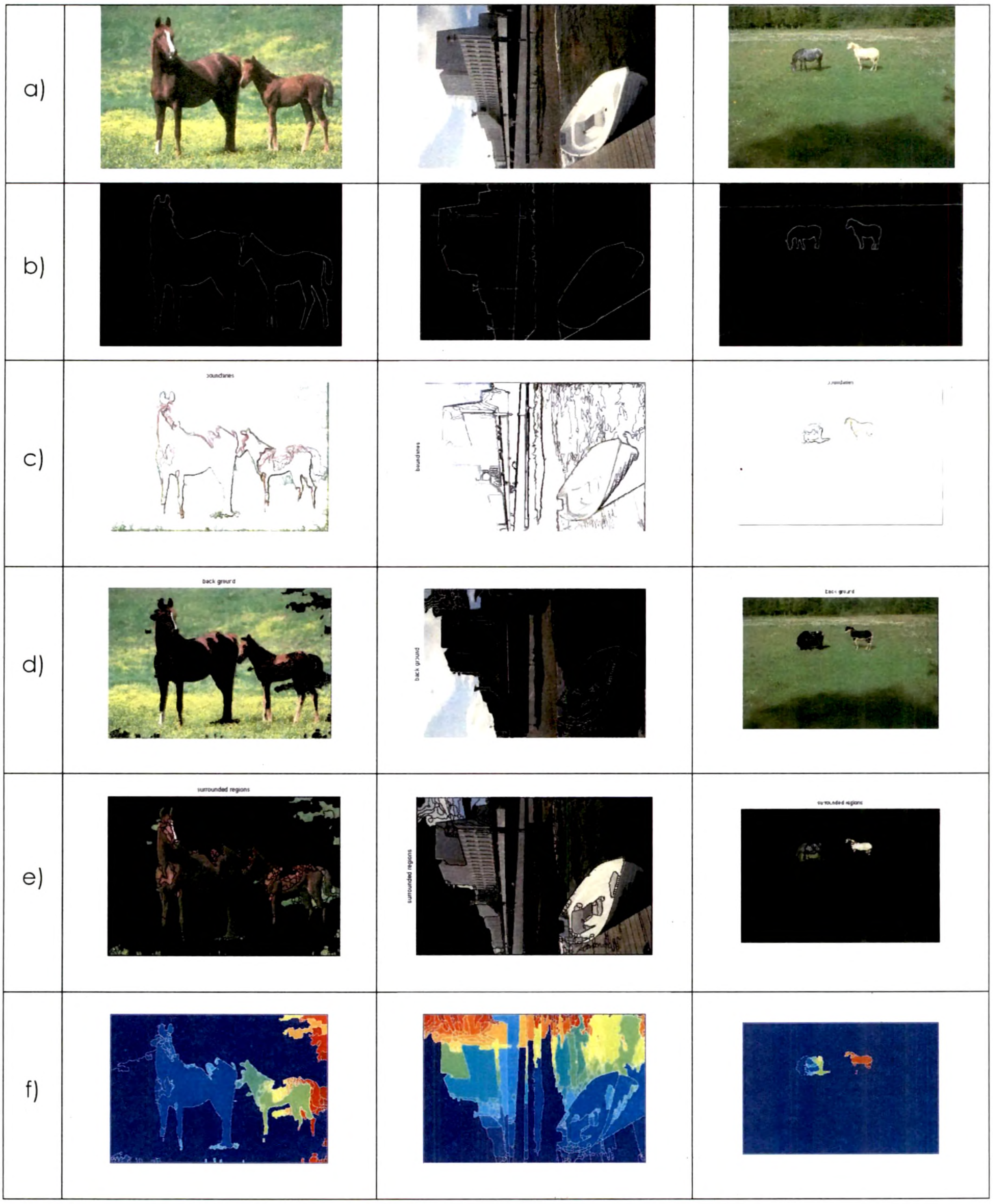


Figure 40. Result comparison: Human segmented images with revealed foreground objects & background, incorporating stationary Haar wavelet decompositions at levels 2. (a) Original images [Fowlkes, on line] [Martin, 2001]. (b) Human segmented images [Fowlkes, on line] [Martin, 2001]. (c) Detected prominent boundaries. (d) Separated background. (e) Revealed foreground. (f) Watershed regions.

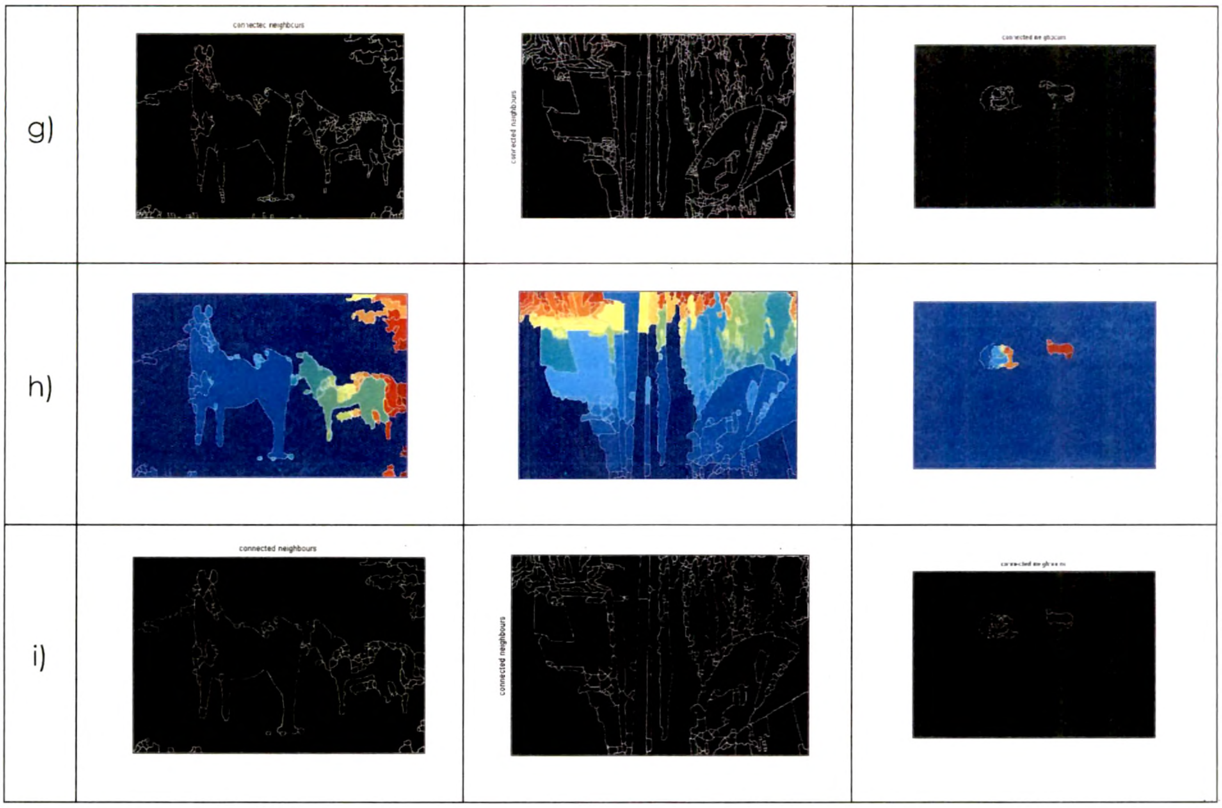


Figure 40 (Contd.). Result comparison: Human segmented images with revealed foreground objects & background, incorporating stationary Haar wavelet decompositions at levels 2. (g) Corresponding watershed pixels of foreground object boundaries. (h) Watershed regions with reduced artifacts. (i) Corresponding watershed pixels of foreground object boundaries.

Figure 41. Result comparison: Human segmented images with revealed foreground objects & background. (a) Original images [Fowlkes, on line] [Martin, 2001]. (b) Human segmented images [Fowlkes, on line] [Martin, 2001].

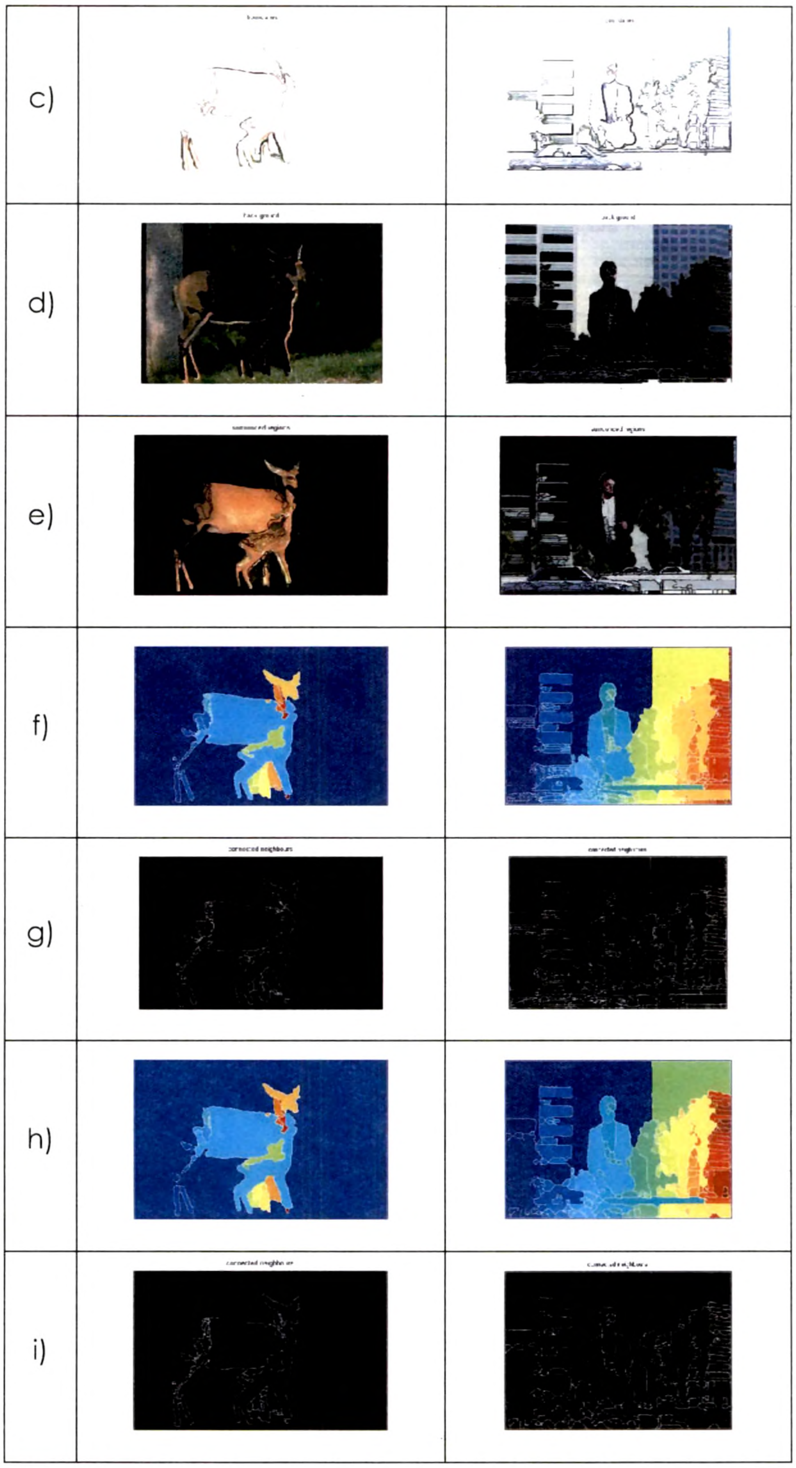


Figure 41 (Contd.). Result comparison: Human segmented images with revealed foreground objects & background. (c) Detected prominent boundaries. Left: Incorporating stationary Haar wavelet decomposition at level 3. Right: Incorporating stationary Haar wavelet decomposition at level 2. (d) Separated background. (e) Revealed foreground. (f) Watershed regions. (g) Corresponding watershed pixels of foreground object boundaries. (h) Watershed regions with reduced artifacts. (i) Corresponding watershed pixels of foreground object boundaries.

5.3.3 Qualitative Result-comparisons: Proposed Method, JSEG & Human Segmented Images of BSDB [Martin, 2001] [Fowlkes, on line]

JSEG algorithm, proposed in [Deng, on line] [Deng, 2001] incorporates color quantization and spatial segmentation stages, where colors of the images are quantized in several color classes to produce class-map of the image in the first step. The class image contains the pixels labeled with the color class. The local window based spatial criterion is applied on class-map to generate multi-scale J-Images which are processed for region growing method leading to segmentation. The values of J-Image represent possible boundaries and interiors of color-texture regions. The algorithm can be applied to still images and video. Despite being a fast-computationally efficient algorithm, JSEG segmentation results are sensitive to various parameters - quantization scale, number of scales and region merge thresholds, a pointed mentioned and illustrated qualitatively in [Deng, 2001] with the help of segmentation results at different parameters. The major limitation of the algorithm, cited in the paper [Deng, 2001] with the remark **"There seems to be no easy solution"**, is to handle shades and smooth transitions due to illumination variations caused by intensity or spatial changes of illumination source.

Following Figures of the section compares results of proposed methods with that of JSEG [Deng, on line] [Deng, 2001] segmentation and human segmented natural images of BSDB [Fowlkes, on line] [Martin, 2001] to illustrate the suitability of proposed method to eliminate the background for extracting the foreground from images possessing variety of background and characteristics. *The JSEG results are obtained with the software available at JSEG site [Deng, on line] for default value of number scale and region merge threshold with quantization threshold specified as 255.*

The well localization of prominent boundaries and effectiveness of foreground extraction has been illustrated in Figure 42 and Figure 43 for images of ALOI database [ALOI, on line] [Geusebroek, 2001] captured under controlled conditions for varied viewing angles, illumination angles and illumination color. Refer Section 6.4 for description and characteristics of the database. The Figure 42 contains images of objects with finer well defined details with illumination changes. And, Figure 43 contains objects with illumination changes producing shadows and intensity variations. Though images included in Figure 42 and Figure 43 contain monotonous gray background making foreground extraction simple, they are included here to show effects of illumination variations produced under controlled conditions on segmentation / foreground extraction.

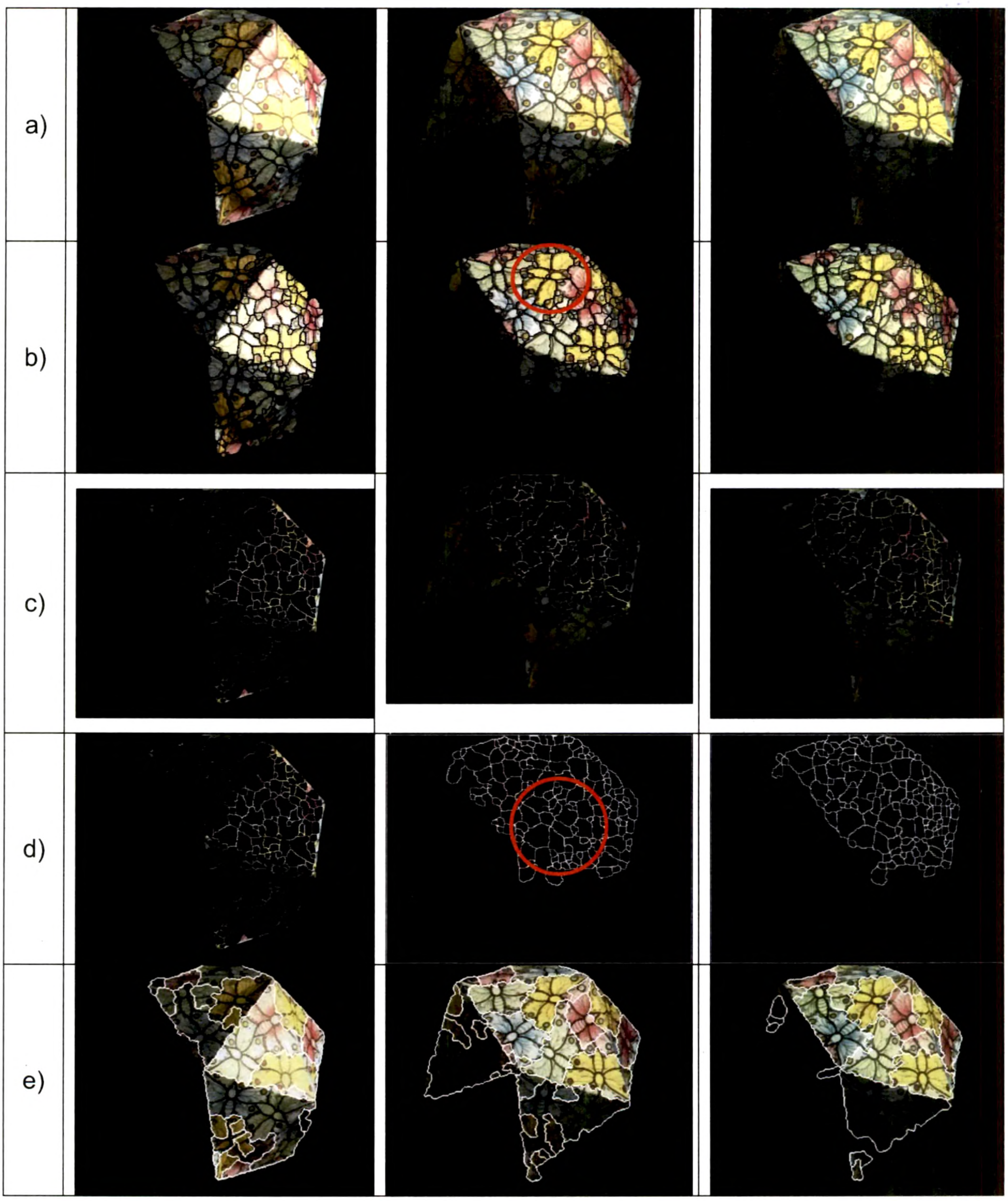


Figure 42 Effect of illumination variations on segmentation / foreground extraction on object with fine details. (a) Original Images [ALOI, on line] [Geusebroek, 2001]. (b) Extracted foreground of (a). (c) Background. (d) Watershed pixels corresponding to (b). (e) Segmentation with JSEG [Deng, on line] [Deng, 2001].

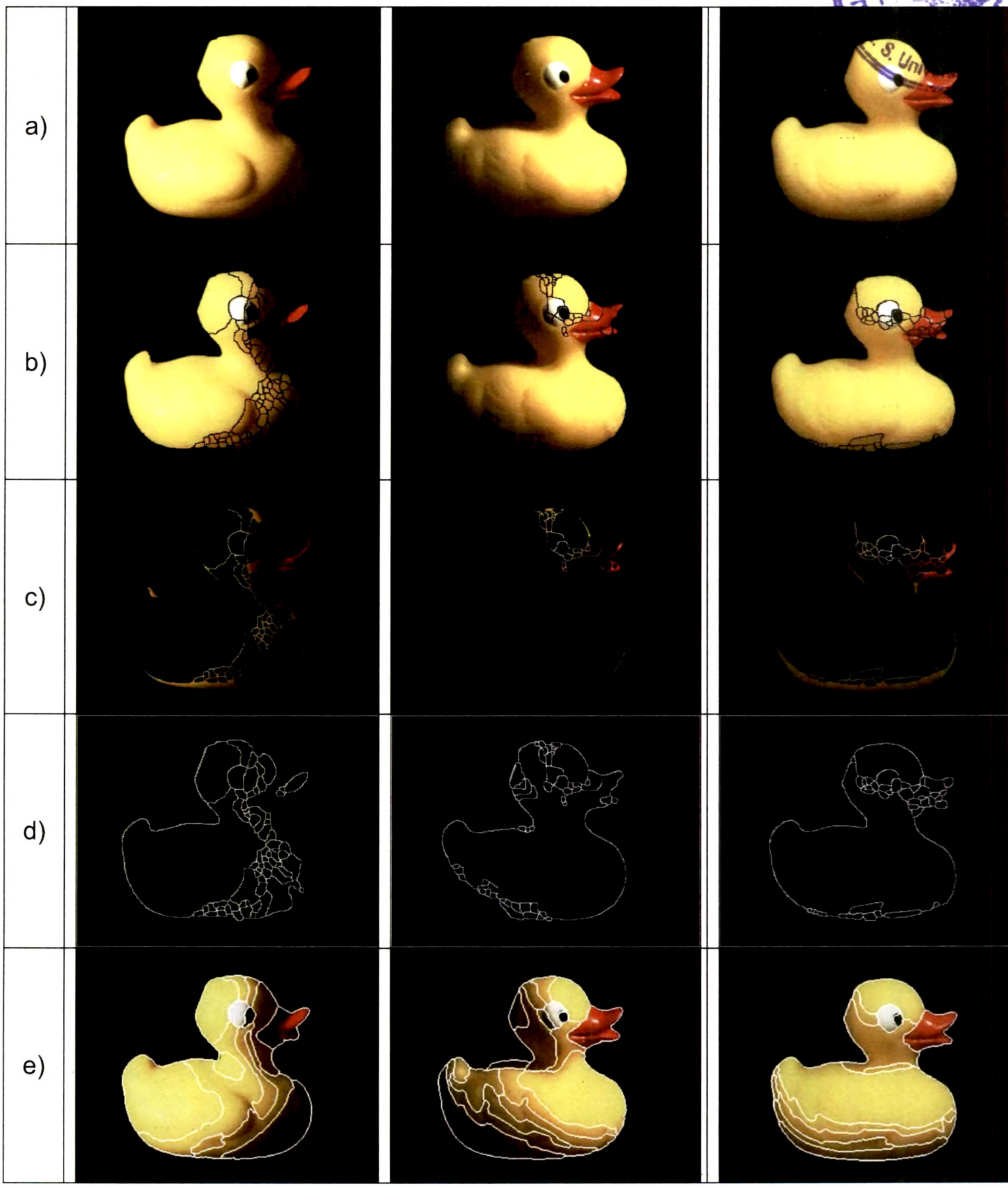


Figure 43. Effect of illumination variations on segmentation / foreground extraction on non-textured object. (a) Original Images [ALOI, on line] [Geusebroek, 2001]. (b) Extracted foreground of (a). (c) Background. (d) Watershed pixels corresponding to (b). (e) Segmentation with JSEG [Deng, on line] [Deng, 2001].

As png file format is not supported by JSEG software [Deng, on line], the jpg equivalent of ALOI images are used in Figure 42 and Figure 43 for JSEG segmentation. The segmentation / foreground extraction results of the proposed method are compared with the results produced with JSEG [Deng, on line] [Deng, 2001]. The finer prominent details are not detected by JSEG - Figure 42 (e), whereas they are marked as prominent boundaries by the proposed method as shown in Figure 42 (d). The boundaries enclosing butterflies are well detected and one such case is encircled and illustrated in Figure 42 (b) and Figure 42 (d).

As illustrated in Figure 43 (e), smooth intensity changes / shadows tend to over-segment regions with JSEG segmentation (the cited limitation in [Deng, 2001]). The spatial and intensity variations resulting into shadows and shades of smooth variations do not significantly alter outer boundaries of the foreground detected with proposed method. The over-segmentation produced around some boundaries due to watershed transformation has no effect on foreground extraction.

The smooth changes and diversities in colors & textures are performance challenging characteristics of natural images for segmentation. The results of segmentation / foreground extraction with proposed method for natural images are shown in Figure 44 to Figure 46 for comparisons with Human segmented images of BSDB [Fowlkes, on line] [Martin, 2001] and segmentation results of JSEG [Deng, on line] [Deng, 2001]. The results and comparison for standard Baboon image is also shown in Figure 44 – Right.

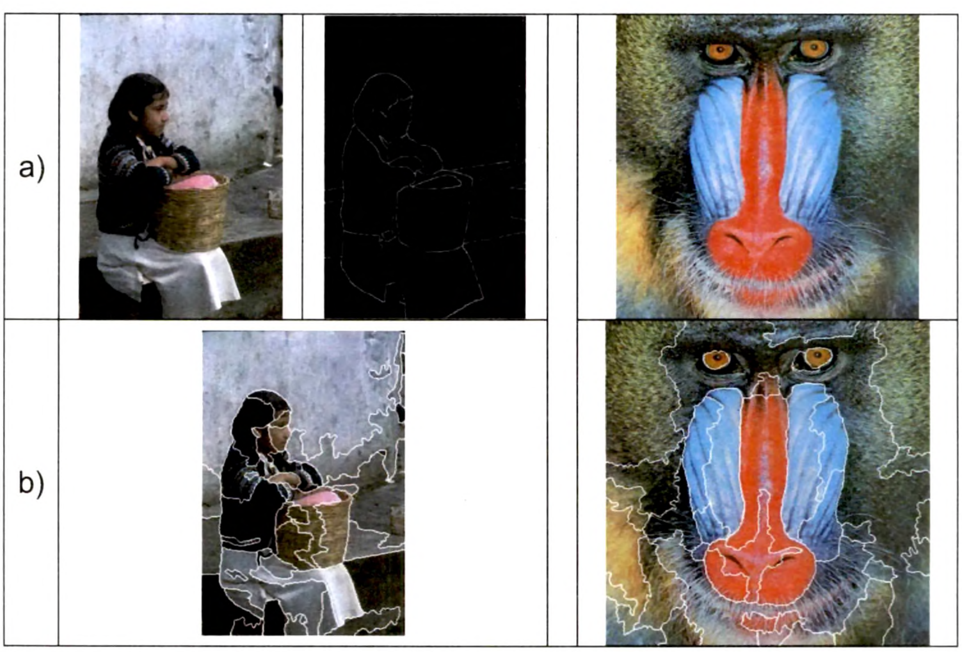


Figure 44. Comparison of segmentation results. (a) Left & Middle - Original and Human segmented Images respectively BSDB [Fowlkes, on line] [Martin, 2001]. (a) Right – Original Baboon image. (b) Segmentation with JSEG [Deng, on line] [Deng, 2001].

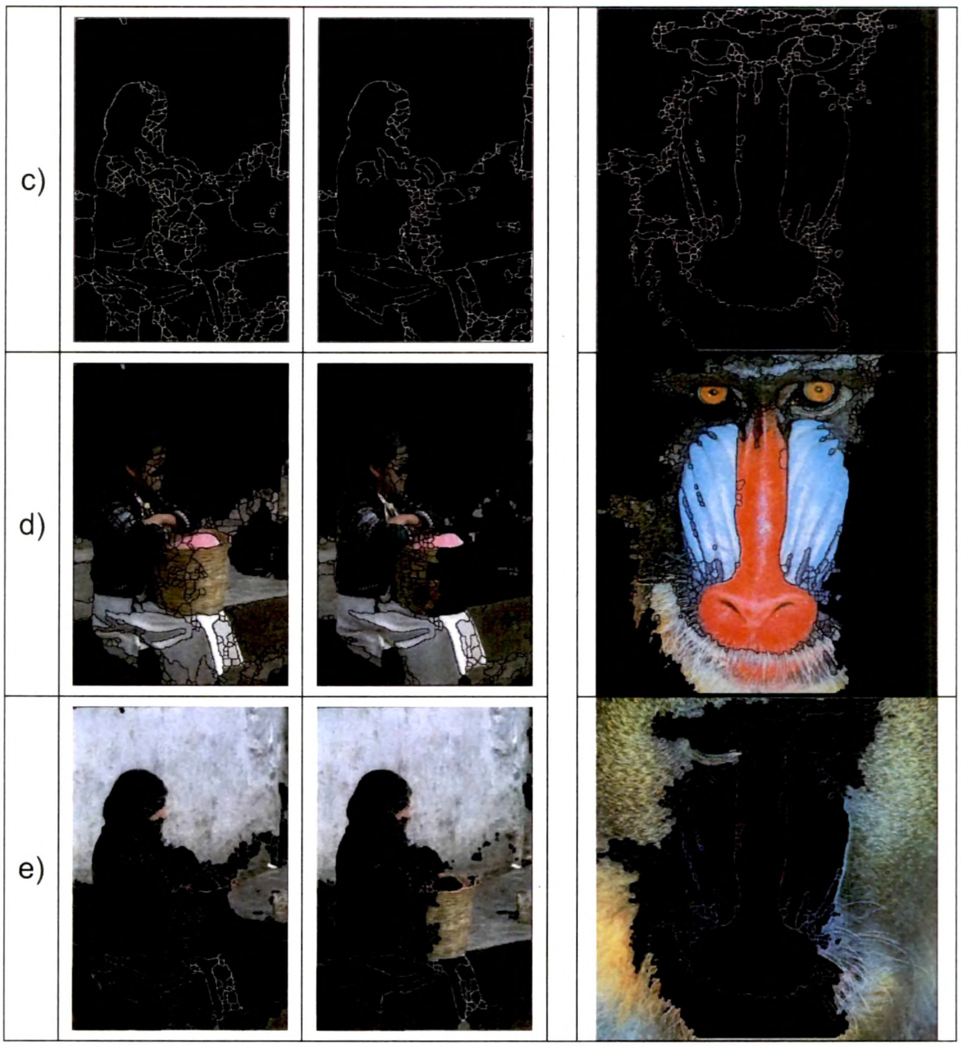


Figure 44 (Contd.). Comparison of segmentation results.. (c) Left & Middle - Watershed pixels with Stationary Haar decomposition at level 1 and level 2 respectively. (c) Right - Watershed pixels with Stationary Haar decomposition at level 2. (d) Extracted foreground. (e) Background.

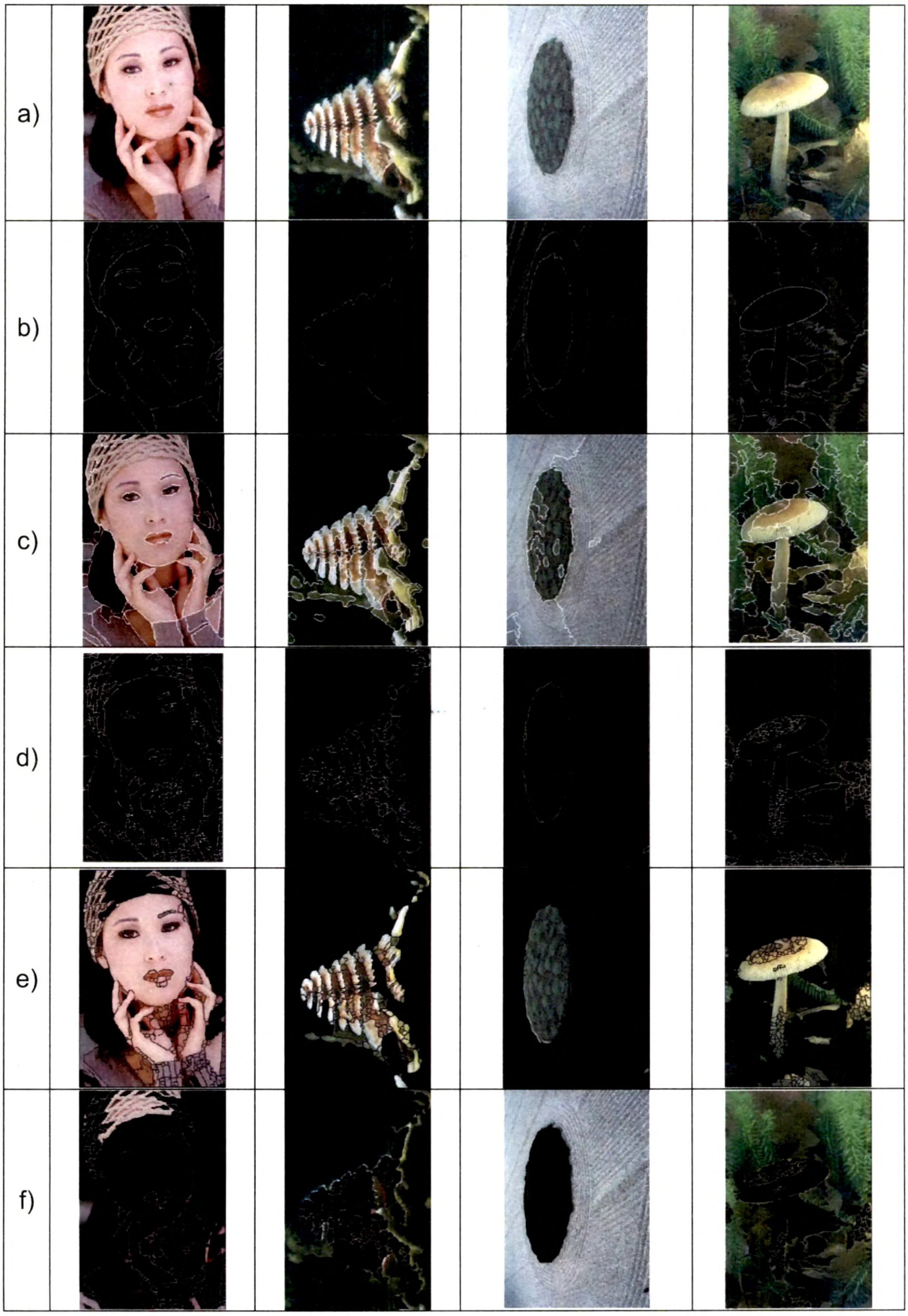


Figure 45. Comparison of segmentation results. (a) Original images BSDB [Fowlkes, on line] [Martin, 2001]. (b) Human segmented Images BSDB [Fowlkes, on line] [Martin, 2001]. (c) Segmentation with JSEG [Deng, on line] [Deng, 2001]. (d) Watershed pixels with Stationary Haar decomposition at level 2. (e) Extracted foreground. (f) Background.

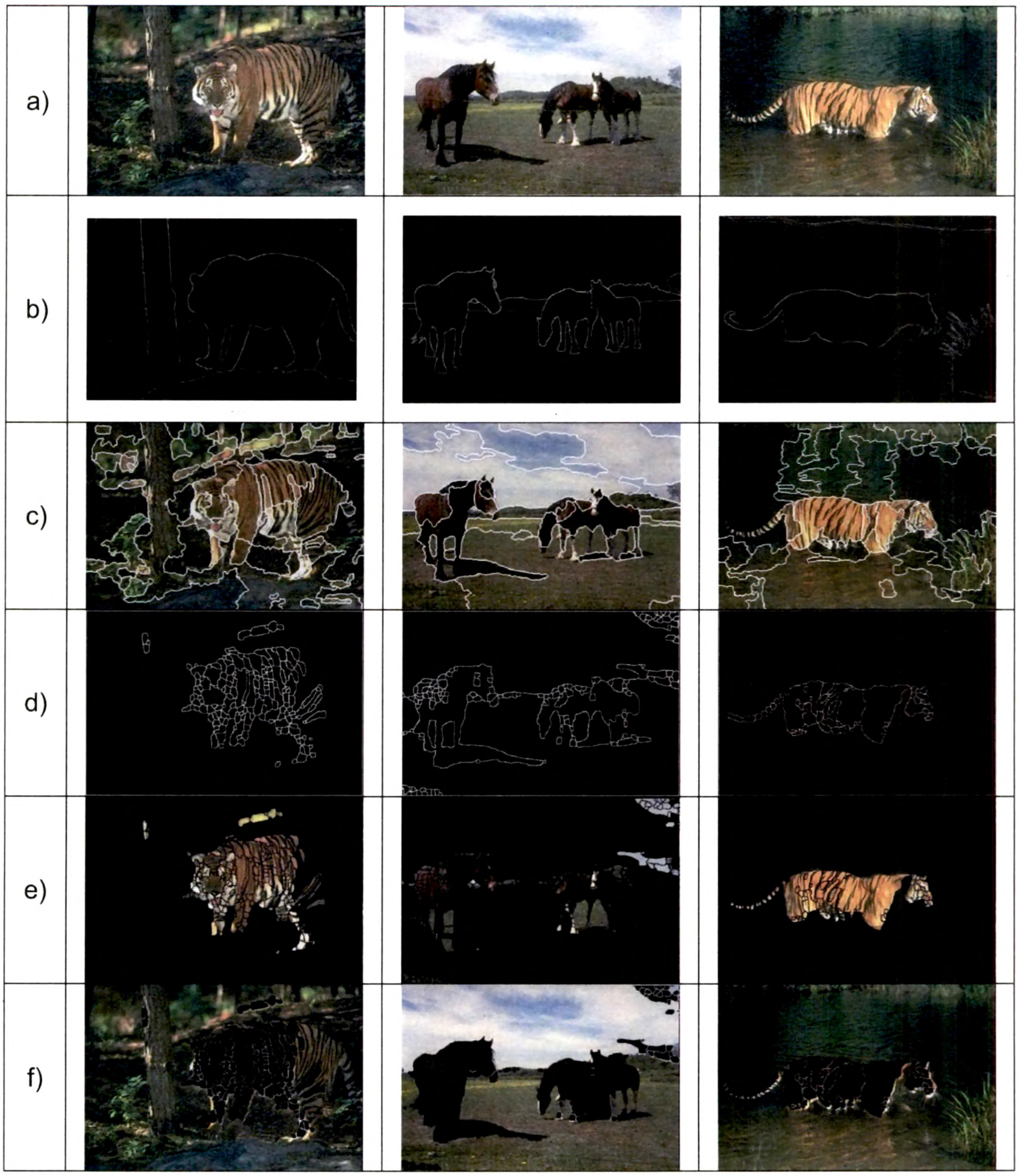


Figure 46. Comparison of segmentation results. (a) Original images BSDB [Fowlkes, on line] [Martin, 2001]. (b) Human segmented Images BSDB [Fowlkes, on line] [Martin, 2001]. (c) Segmentation with JSEG [Deng, on line] [Deng, 2001]. (d) Watershed pixels with Stationary Haar decomposition at level 2. (e) Extracted foreground. (f) Background.

5.4 Discussion

- The proposed method addresses the issue of proper segmentation by enforcing reliable processing of low level cues for avoiding breaks as well as under segmentation by utilizing continuity preserving, well localized visually prominent boundaries for foreground – background separation. The problem of over segmentation is overcome by compositely considering proximity influence and watershed algorithm.
- The method results are tested on variety of images including those of natural images, synthesized images, human faces etc. with diversified textures. The effectiveness of the method is proved for low as well as high resolution images and for size- reduced images by a large factor. The artifacts in watershed regions are significantly reduced, producing less number of small sized regions.
- The foreground extraction results are largely insensitive to illumination variations produced by changes of intensity and spatial locations of the light sources. Thus, the proposed method addresses the issue to the remark **"There seems to be no easy solution"** cited by Deng et al. in [Deng, 2001].
- The watershed artifacts around some portion of boundaries do not affect the foreground boundaries.
- The detected foreground object boundaries are well-localized and well-delineated. The precise processing leading to detection of prominent boundaries & enclosing boundaries of finer prominent details of even small objects is well illustrated in Figure 42.
- The stationary Haar wavelet decomposition at various levels makes the approach suitable for multi-scale hierarchical image segmentation for effective foreground separation and region features extraction. Stationary Haar decomposed image at higher level delineates objects having perceptually superior prominent boundaries. The results of objects revealing for images with poorly defined prominent boundaries are better with exclusion of Haar decomposition step of the method, as illustrated in Figure 35 - Left.

- The results of background separation revealing foreground objects are not affected due to inter- texture and intra-texture variations as presented in Figure 34 to Figure 41.
- For some cases, regions attached to objects of foreground alter the shape of foreground region.
- The extracted region-features and shape features may be utilized for object identification, content based image retrieval, automatic image tagging, and visual scene analysis.
- The proposed method has been tested on a set consisting of about 400 images covering representative images of different categories possessing a wide variety of salient characteristics. The produced results are effective for benchmark database images of Berkeley Segmentation Dataset images [Fowlkes, on line] [Martin, 2001] and SIMPLIcity database images [Wang, 2001] [SIMPLIcity, on line] and are comparable with human segmented images of BSDB [Fowlkes, on line] [Martin, 2001].
- The quantitative comparisons of the results of proposed method for foreground extraction have been carried out with performance measures $Precision_{fg}$ and $Recall_{fg}$, computed with respect to Ground Truth foreground and presented in Annexure 4 endorses the uniqueness & effectiveness.

5.5 Concluding Remark

Precise processing for detection of prominent boundaries consequently leading to exclusion of background reveals foreground and associated features for image retrieval...