4. Edges & Prominent Boundaries Detection

4.1 Introduction

The chapter covers proposed novel method for detecting perceptual-edges and the qualitative comparison of results with edge response of leading tools Adobe Photoshop, MS Photo Editor and ACD Photo Editor. The method results for detection of edges and thin edges, incorporating different levels of stationary Haar wavelet decompositions are compared, analyzed and presented. The method results outperform others detecting perceptually significant edges, proving its suitability for edge features extraction, object detection & identification. The thinned edges can be utilized further to reduce over-segmentation produced by watershed transformation, suggested as one of the future enhancements of the proposed work.

The later portion of the chapter includes a proposed novel method for categorizing visually prominent and non-prominent boundaries from candidate boundaries by considering prominence measures. The method results for various categories of images inclusive of standard databases [Fowlkes, on line] [Martin, 2001] [Wang, 2001] [SIMPLIcity, on line] [Everingham, on line] [MedPics, on line] are presented and qualitatively compared with human segmented images of standard database [Fowlkes, on line] [Martin, 2001]. The reliable processing of low level color cues results into precise, well localized formation of prominent boundaries.

4.1.1 Key Terminologies

Contours: Contours are closed curves defining points of equal altitude (height/level). For a given channel, contours are generated by finding contour vertices (xi, yi) such that they form a closed curve and are at the same altitude. Here altitude for a channel under consideration refers to value of R / G / B / Gray component. For individual channel, the input matrix is treated as a regularly spaced grid, with each element connected to its all 3 neighbors forming a surface. These 4 neighbors constitute a cell.

At given height, contour vertices are found by performing a linear interpolation to locate the point at which the contour crosses the edges of the cell. Such contours at different and multiple heights are found & processed for all 4 channels. Figure 16 shows contours for respective channels.

Proximity influence: Proximity influence is a unit influence induced by a contour vertex to its nearest neighboring pixel. There can be multiple contour-vertices near a given pixel. Thus, prominence measure at a given pixel is proportionate to total proximity influence induced by all such contour vertices. Such measure is computed for all pixels of the image. E.g., let us consider two contour 1 & contour 2. Say, contour vertices A & B are on contour 1 and contour vertices P & Q are on contour 2. If M (x, y) is the nearest pixel of B; N(x-1, y-1) is the nearest pixel of say A & Q both; and O(x , y-1) is the nearest pixel of P then, B will induce proximity influence on M; A & Q will induce proximity influence on N; and similarly P will induce on O.

4.2 Block Diagram – Edges and Prominent Boundaries Detection

The block diagram for edges detection and prominent boundaries detection methods utilizing Stationary Haar wavelet based decomposition at various selected levels, contour detection at multiple levels and prominence measures is shown in Figure 14. The selection of wavelet level is performed with the help of GUI (Graphical User Interface). The level is to be selected based on image characteristics, categories, resolution and scale of segmentation. Lower level Haar results in to more number of contours / edges. E.g. Figure 20 (d) contains more edges compared to that of Figure 20 (g) detected with Haar SWT at level 1 and level 2 respectively.

After reading required input selected by user with GUI in first block, the next block performs basic operation of color channel separation. The wavelet decomposition at selected level is performed by the respective block. The contours at multiple levels are detected and processed for all four channels as explained in Section 4.1.1.

The prominence measure is utilized for edge detection and prominent boundaries detection as shown below. The block named Prominence Measure Computation of Figure 14 takes input from Contour Detection & Processing block and finds Prominence measure for all pixels for all four channels.

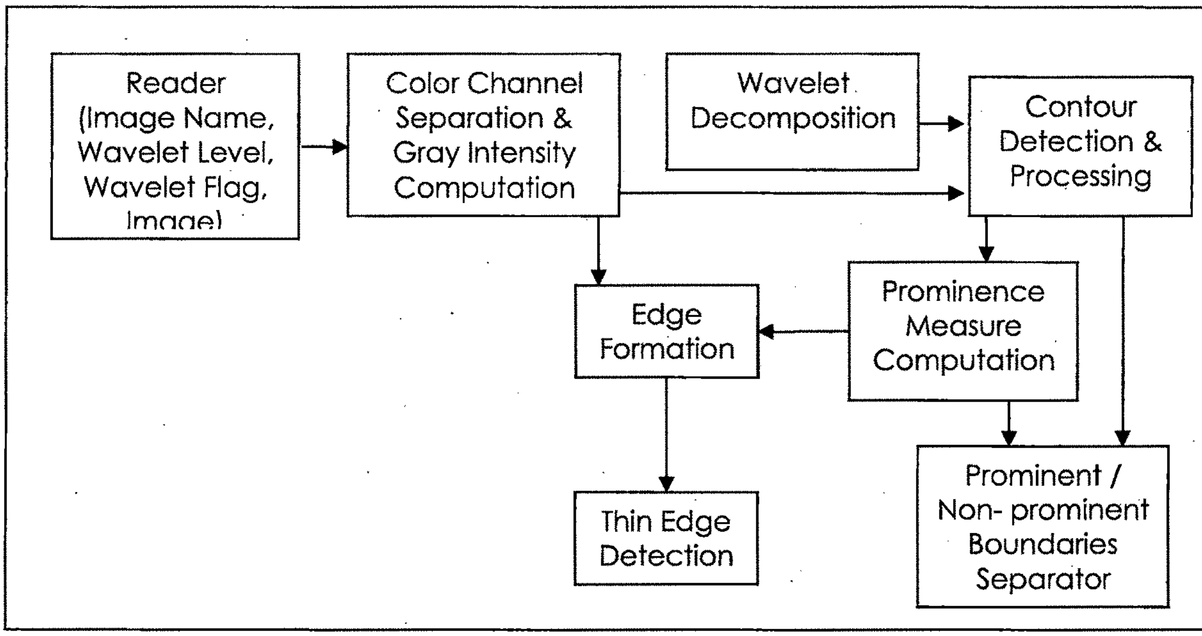

Figure 14. Block Diagram – Edge and Prominent Boundaries Detection.

4.3 Edge Detection

The local color cue based candidate boundary detection incorporating stationary Haar wavelet decomposition at various levels and thresholded prominence measures are used for detecting edges in color images in the proposed method. The non-homogeneous inter-tuples and non-uniform intra-tuple contributions of RGB tuples for conception of perceptual-edges are exploited in the edge detection method from candidate boundaries for color images. Refer Figure 16 and Figure 17 for example. The table-top boundaries in the original image are perceptually significant, as can be seen in the original image of Figure 15 (a). The intra tuple values and inter tuple values of pixels constituting these boundaries are such that the Red channel contributes the least for forming the perceptually significant edges as shown in the Figure 17 (a) left, corresponding to edges for Red channel where in table-top edges are not well defined. The Algorithm 1 exploits this characteristic of non-uniform contribution (without actually measuring it) to enforce four channel-processing to yield reliable processing.

Many state of the art techniques for image content analysis are enforcing reliable and precise processing of low level cues for extracting features, as that has been proved to be very critical for over-all performance of the applications. The edges in the image can be treated as primitive features useful for deriving other features like contours, regions & object boundaries, shapes etc. The performance of edge detection method is challenged by image characteristics like image resolution, textures, variations in illumination etc.

The traditional gradient based edge detection techniques which examine a set of pixels for abrupt intensity changes are characterized by generation of large number of edges due to textures or color variations ending up into a difficult task of linking edges for forming boundaries by minimizing over segmentation. The state of the art techniques examine color and / or texture channels for edge detection forming boundaries / contours / regions finally leading to image segmentation. The proposed method addresses the problem in a hierarchical framework and incorporates stationary Haar wavelet decompositions at various levels, candidate boundaries and proximity influence for edge detection. The candidate boundaries and thresholded prominence measure produce edges which are not necessarily thin. These detected edges are thinned by performing a series of morphological operations of Matlab R14 on thresholded prominence measure. The local color cues used to form candidate boundaries ensures reliable processing of low level cues. The results are qualitatively compared with edge detection response of leading DTP and image processing tools for i) detection of perceptually significant edges ii) elimination of insignificant edges iii) detection of edges pertaining to region / object boundaries iv) preservation of continuities of detected edges on images of databases [Fowlkes, on line] [Wang, 2001] [SIMPLIcity, on line].

4.3.1 The Method

The multi-resolution signal decomposition as wavelet representation and the extension of orthogonal wavelet representation for images was proposed with mathematical model for computation and interpretation in [Mallat, 1989]. The classical Discrete Wavelet Transform (DWT) convolves the signal with appropriate low and high pass filters followed by decimination operation to keep generally even indexed elements and discard others by halving number of elements at each stage. The stationary Wavelet Transform (SWT) as proposed in [Nason, 1995], convolves signal with appropriate high pass and low pass filters without performing decimation operation for producing two sequences for the next level. The shortcoming of shift-invarientness of DWT is overcome in the SWT [Nason, 1995]. The proposed method makes use of stationary Haar wavelet transform at various levels [Mallat, 1989] [Nason, 1995]. Refer to

Section 3.2 for related technical details. Equations 3.1 and 3.2 describe the Haar mother wavelet function $\psi(x)$ and its scaling function $\varphi(x)$ respectively.

The method uses RGB color model. As analyzed empirically, the contribution of RGB tuples for constituting boundaries is non-homogeneous inter-tuples wise and non-uniform intra-tuple wise. The candidate boundaries are closed contours of pixels forming perceptually significant and insignificant boundaries, incorporating decomposition of the image into approximate and detailed (vertical, horizontal & diagonal) coefficients by applying stationary Haar wavelet transform at various levels for RGB color and gray channels. The prominence measure based edge detection is followed by morphological operations to get thinned image of one pixel width. The steps of the proposed method for detecting edges and thinning of edges are as under. Refer Figure 14 for corresponding block diagram.

Step 1: Read Image name, wavelet decomposition level, and wavelet flag selected by a user with the help of Graphical User Interface.

Step 2: Read RGB color image $I(x, y, z)_{m \times n \times 3}$. Separate each color channel. Compute intensity values for gray channel of the image.

Step 3: If wavelet flag is 1, resize image for height and width to make them integer power of 2 by zero padding.

Step 4: If wavelet flag is 1, apply stationary Haar wavelet transform at given level to decompose R, G B & Gray color channels, into approximate and detailed coefficients. Let us denote them as A^j, H^j, V^j and D^j as approximate coefficients, horizontal, vertical & diagonal detailed coefficients respectively at level j for given color channel c, where $0 < c < 5$.

$$Z_c^j = \{A^j, H^j, V^j, D^j\},\ j>0.$$

Step 5: Initialize prominence measure to zero

$$U(x, y) = 0$$

For First color channel and wavelet decomposed image,

Step 6: Find contours at multiple levels.

Let such set be $C_{ck} = \{(x_i, y_i)_k\}$, i, k > 0.

(Refer Figure 15 for the results.)

Here, k denotes index of a contour,

i denotes index of a vertex for a given contour C_k

Step 7: Merge all contours into one data structure.

Find length of each contour.

L_{ck} = length (C_{ck}).

Exclude contours having $L_{ck} <$ contour_length_threshold.

Call remaining contours as candidate boundaries, denoted as C'_{ck}.

(Refer Figure 16 for the results.)

Here merging refers to storing of contours of all different levels into cell data structure.

Step 8: Update prominence values U(x, y) at all pixels for all vertices of C'_{ck}.

Each vertex of C'_{ck} induce proximity influence to its nearest neighboring pixel. Prominence value at given coordinate (x, y) gives total of induced proximity influence.

Step 9: Map C'_{ck} to produce binary image consisting of on pixels corresponding to the vertices of C'_{ck}. (Refer Figure 17 for the results.)

Step 10: Repeat steps 6 to 9 for all channels.

Step 11: Apply operator χ to threshold and map U(x,y) on the image I(x, y, z) to get edges-mapped image I'(x, y, z) and binary image BW(x,y), given as

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

$I'(x, y, z) = I(x, y, z)$, if $U(x, y) >$ prominence_threshold

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

$BW(x, y) = 1$, if $U(x, y) >$ prominence_threshold

and $BW(x, y) = 0$, otherwise.

(Refer Figure 18 (a) Right for the results.)

Step 12: Perform thinning and bridging morphological operations to get thinned image, given by

$BW(x, y) = \wedge BW(x, y)$

Where $\wedge$ denotes thinning and bridging morphological operator. Thinning operation is to thin objects to lines by removing pixels so that an object without holes shrinks to a minimally connected stroke. Bridging operation bridges unconnected pixels, that is, sets 0-valued pixels to 1 if they have two nonzero neighbors that are not connected.

(Refer Figure 18 (b) Left for the results.)

Algorithm 1. Edge detection and thinning

The step 2 and step 3 are omitted if wave flag is set to zero and remaining steps are performed on RGB and gray channels without performing wavelet decomposition.

Thus, the method considers prominent boundaries and proximity influence induced of all four channels for edge and thin-edge detection. The method is novel for detecting edges from candidate boundaries by considering proximity influence. The approach eliminates insignificant edges and detects significant ones. Its suitability for hierarchical approach using SWT permits multi-resolution analysis required for images of different characteristics. The produced results are better than those produced with professional softwares for detecting visually significant edges.

4.3.2 Step-wise Results of the Method

The stepwise results are shown below for an image of Pascal image database [Everingham, on line].

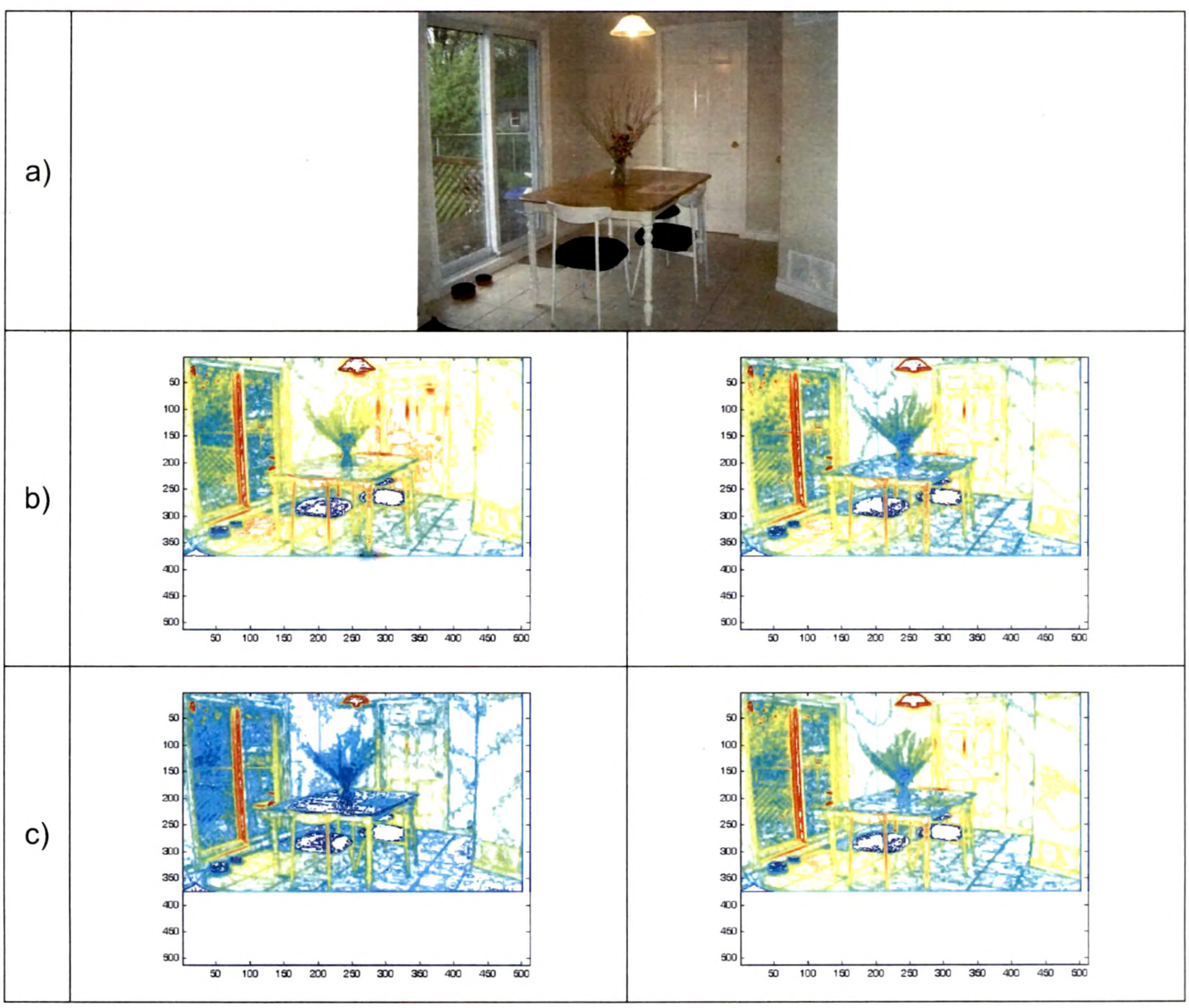

Figure 15. Contour Detection . (a) Original Image [Everingham, on line]. (b) Left, (b) Right, (c) Left, (c) Right: Contours of Red, Green, Blue and Gray channels respectively.

The image depicted to illustrate the results possesses multiple typical challenging characteristics like multiple sources of lights – point and distributed, producing illumination variations, shadows & reflection of light, different texture zones with illumination, color & color tone variations, combination of typical colors of regularly & irregularly shaped natural & man-made objects. The detected contours for RGB and gray channels are shown in Figure 15. The detected contours are large in numbers and densely placed, particularly in textured regions. The location changes of many contours produced in different channels should be noted, implying i) non-uniform contribution of different color channels for constituting prominent-real boundaries ii) one of the causes for over-segmentation.

The Figure 16 shows results of processed contours of Figure 15 obtained by eliminating very small contours produced due to textures or slight variations in intensity. The elimination of such small contours is visually apparent in the textured zones of the image.

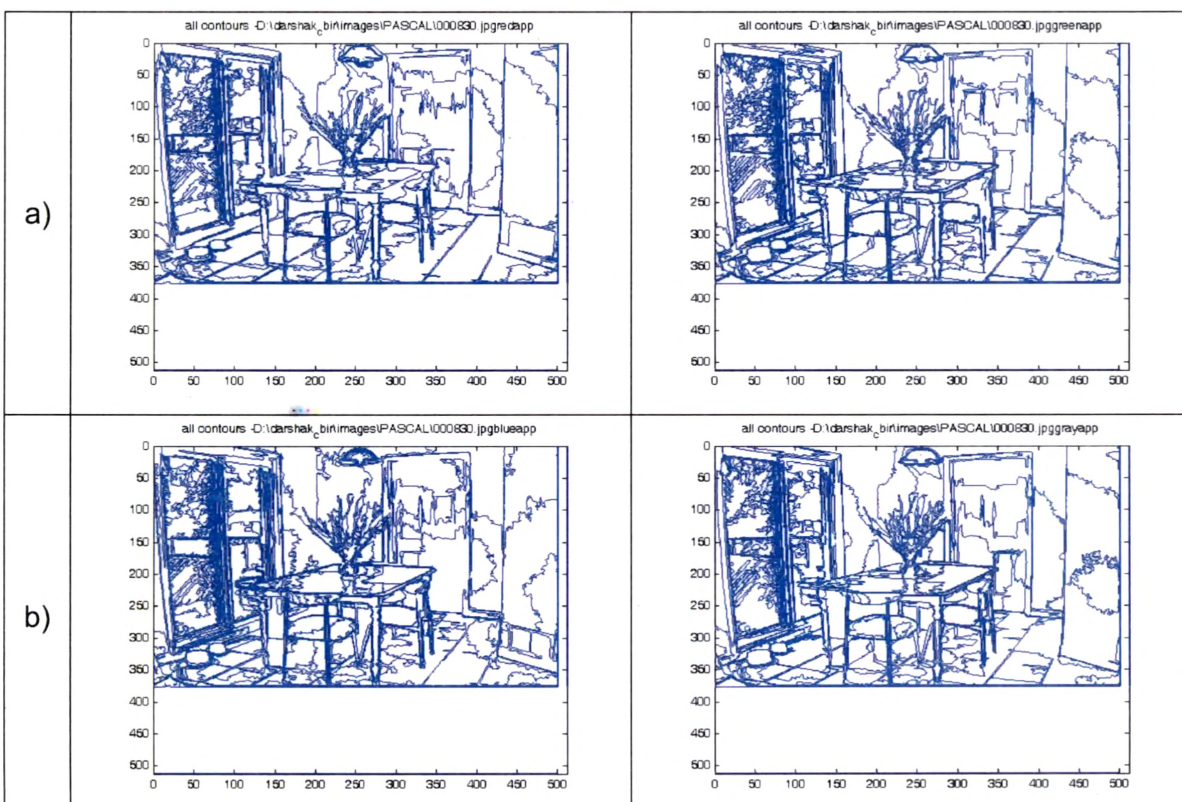

Figure 16. Processed Contours – Candidate boundaries. (a) Left, (a) Right, (b) Left, (b) Right: for Red, Green, Blue and Gray channels respectively.

The vertices of processed contours of all channels are mapped to form binary images as shown below in Figure 17. An attempt to combine these binary output images to a single image for segmentation will lead to over-segmentation of the image.

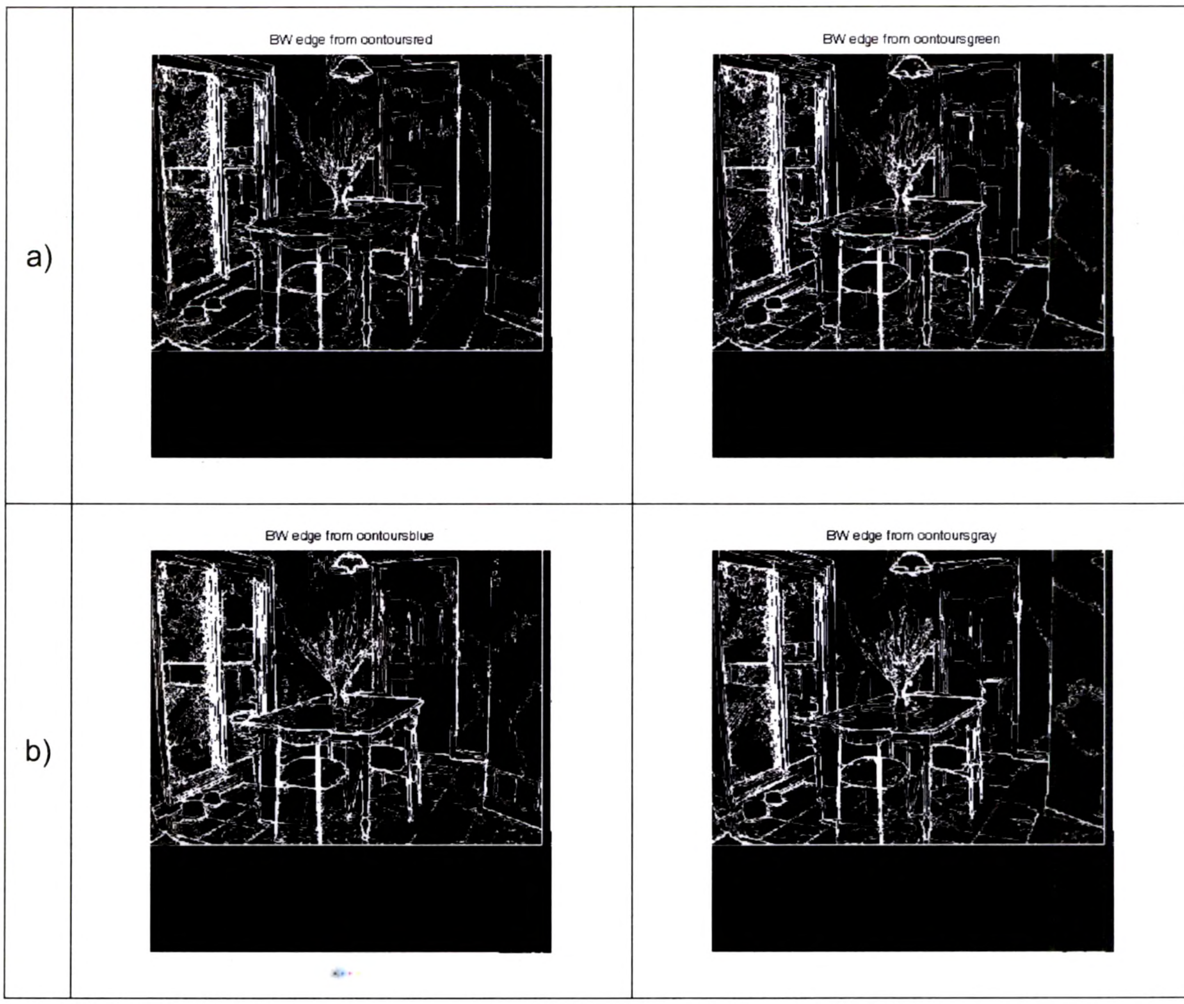

Figure 17. Binary Images: Edges from contours. (a) Left, (a) Right, (b) Left, (b) Right: for Red, Green, Blue and Gray channels respectively.

The Figure 18 (a) Left is the binary image produced by thresholding prominence measure which is mapped to image as shown in Figure 18 (a) Right. Note that the contrasts of Figure 18 (b) are altered manually for clarity in presentation. The morphological operations – thinning and bridging produces thinned image of one pixel width as shown in Figure 18 (b) Left. The Canny edge detection response on binary equivalent of thresholded prominence measure is shown in Figure 18 (b) Right for the comparison.

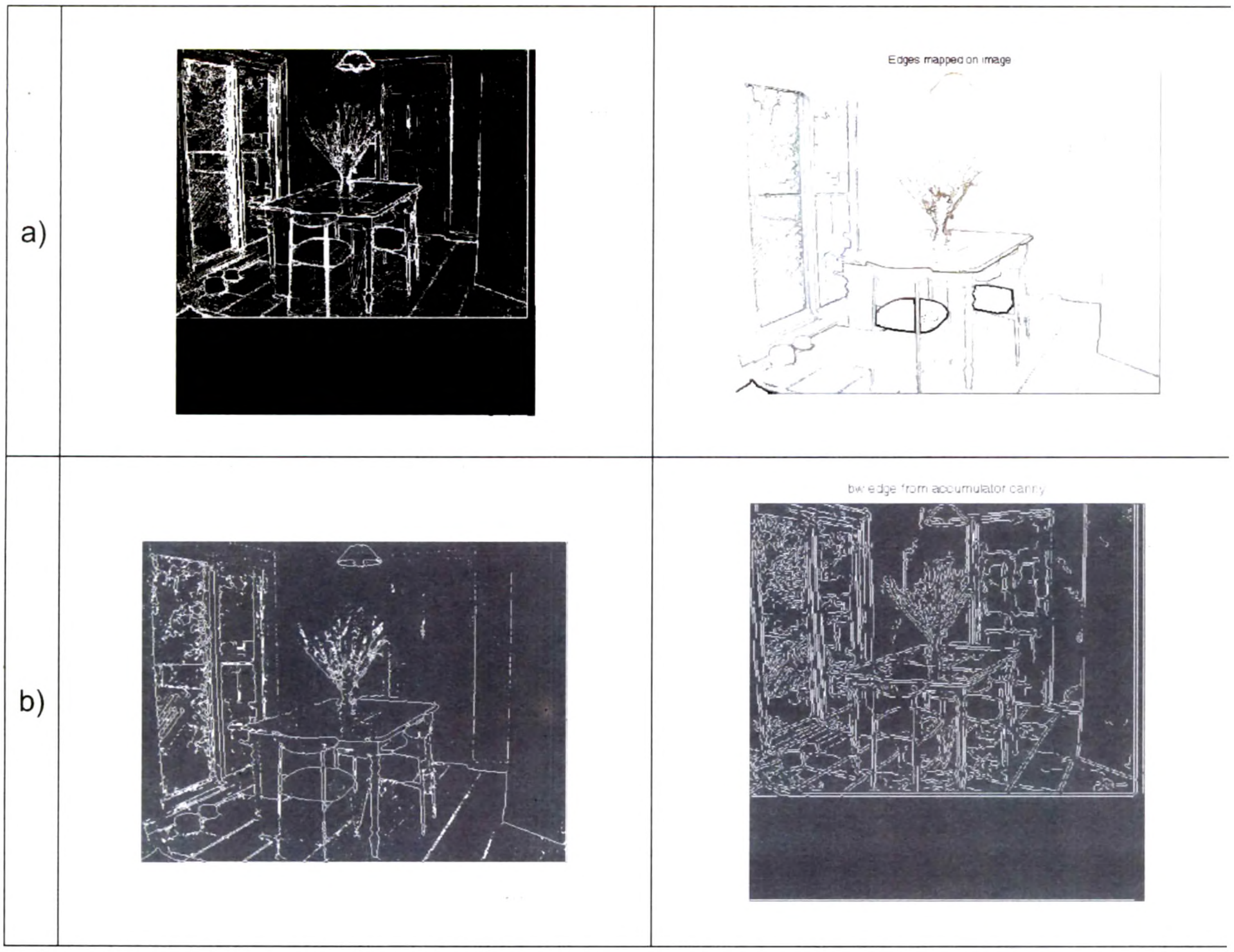

Figure 18. Edges. (a) Left: Thresholded prominence measure. (a) Right: Edges- mapped on image. (b) Left: Thinned edges. (b) Right: Canny edge detection.

4.3.3 Results – Edge Response Comparisons

The results for representative test images are shown in Figure 19 to Figure 21 for qualitative comparisons with the edge detection response of various leading software tools. The candidate boundaries of only gray channel, mapped on images are shown in all Figures. The edge and thin edge detection response take into account candidate boundaries and proximity influence of all channels. Figure 19 and Figure 20 show result-comparison for stationary Haar wavelet decompositions at levels 1 & 2 whereas Figure 21 gives qualitative comparison of results for stationary Haar wavelet decomposition at levels 2 & 3 with those of ACD Photo Editor, Adobe Photoshop and MS Photo Editor. Figure 20 (d) and Figure 20 (g) are corresponding thinned edges obtained from detected edges by applying Stationary Haar wavelet at level 1 and level 2 respectively.

Similarly, Figure 21 (d) and Figure 21 (g) are corresponding thinned edges obtained from detected edges by applying Stationary Haar wavelet at level 2 and level 3 respectively. The salient characteristics of representative test images are listed in Table 2.

Table 2. Test Images & Their Performance Challenging Salient Characteristics.

Figures	**Salient characteristics**
19 (a) - Left	Low resolution natural image of SIMPLIcity [Wang, 2001] [SIMPLIcity, on line] database; Presence of two distinct background regions; one forming high contrast with the fore-ground object whereas the second forming low contrast with the fore-ground object; Inter-region illumination variations.
19 (a) Right	Low resolution natural image of SIMPLIcity [Wang, 2001] [SIMPLIcity, on line] database; Presence of significant intra-object edges; Smooth color variations.
20 (a)	Resized image – 1/10 of original high resolution image captured by an amateur; Textured back-ground; Smooth color variations in the foreground objects.
21 (a)	Higher resolution image [Fowlkes, on line] [Martin, 2001]; Presence of variety of texture zones. Presence of large number of perceptually significant as well as insignificant edges; Inter-region illumination variations.

a)

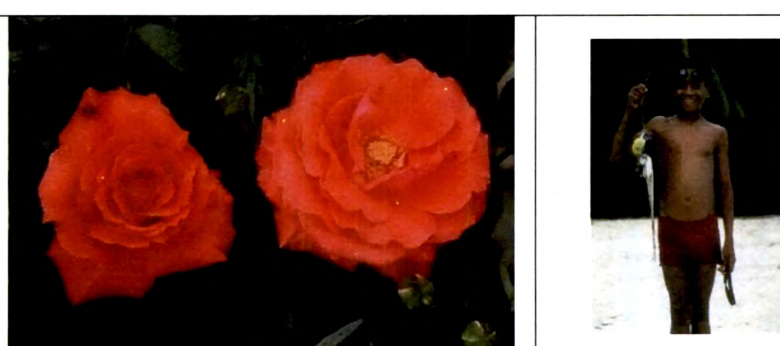

Figure 19. Edge Response Comparison. (a) Original images [Wang, 2001] [SIMPLIcity, on line].

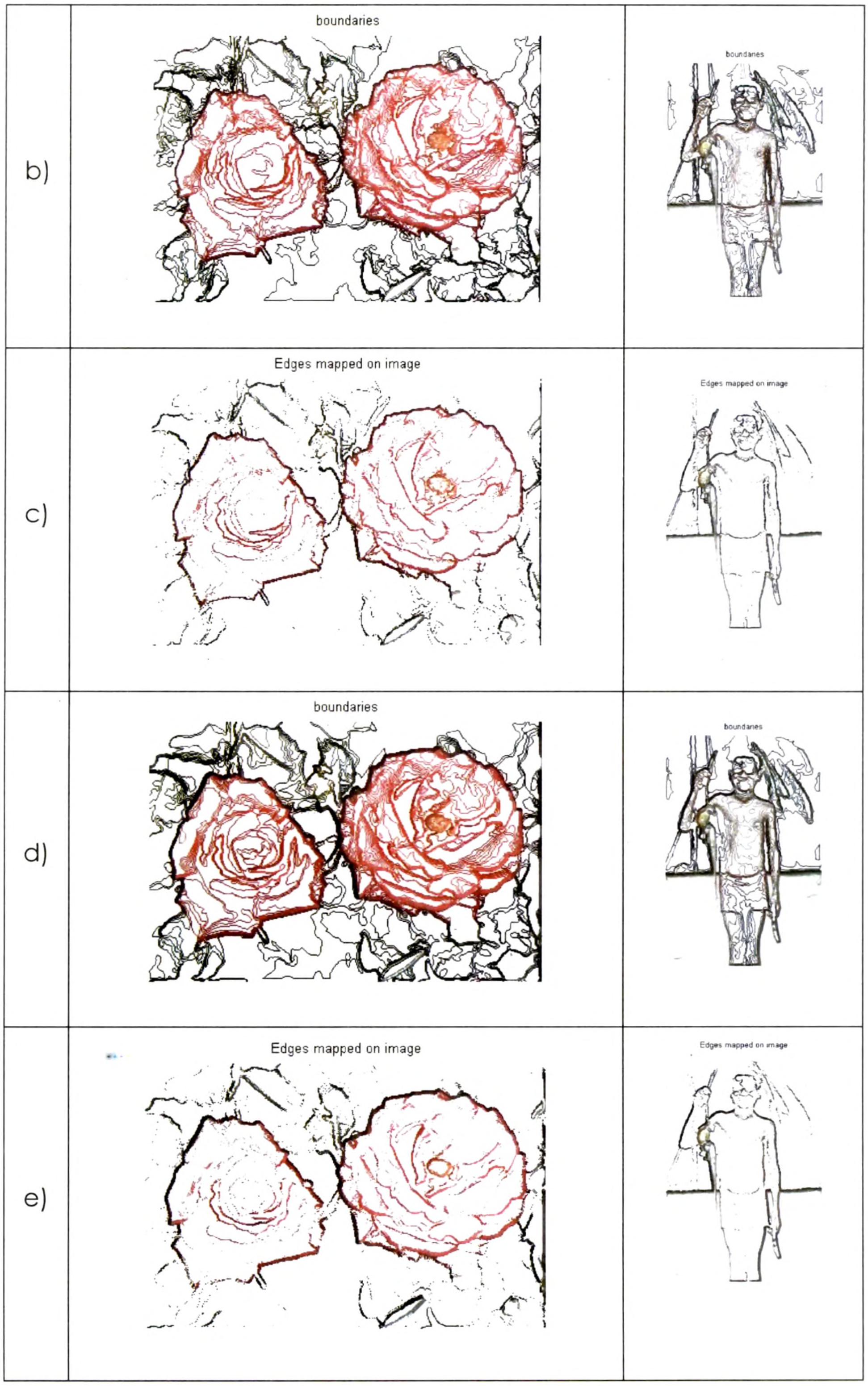

Figure 19 (Contd.). Edge Response Comparison. (b) Candidate boundaries incorporating stationary Haar decomposition at level 1. (c) Detected edges from (b). (d) Candidate boundaries incorporating stationary Haar decomposition at level 2. (e) Detected edges from (d).

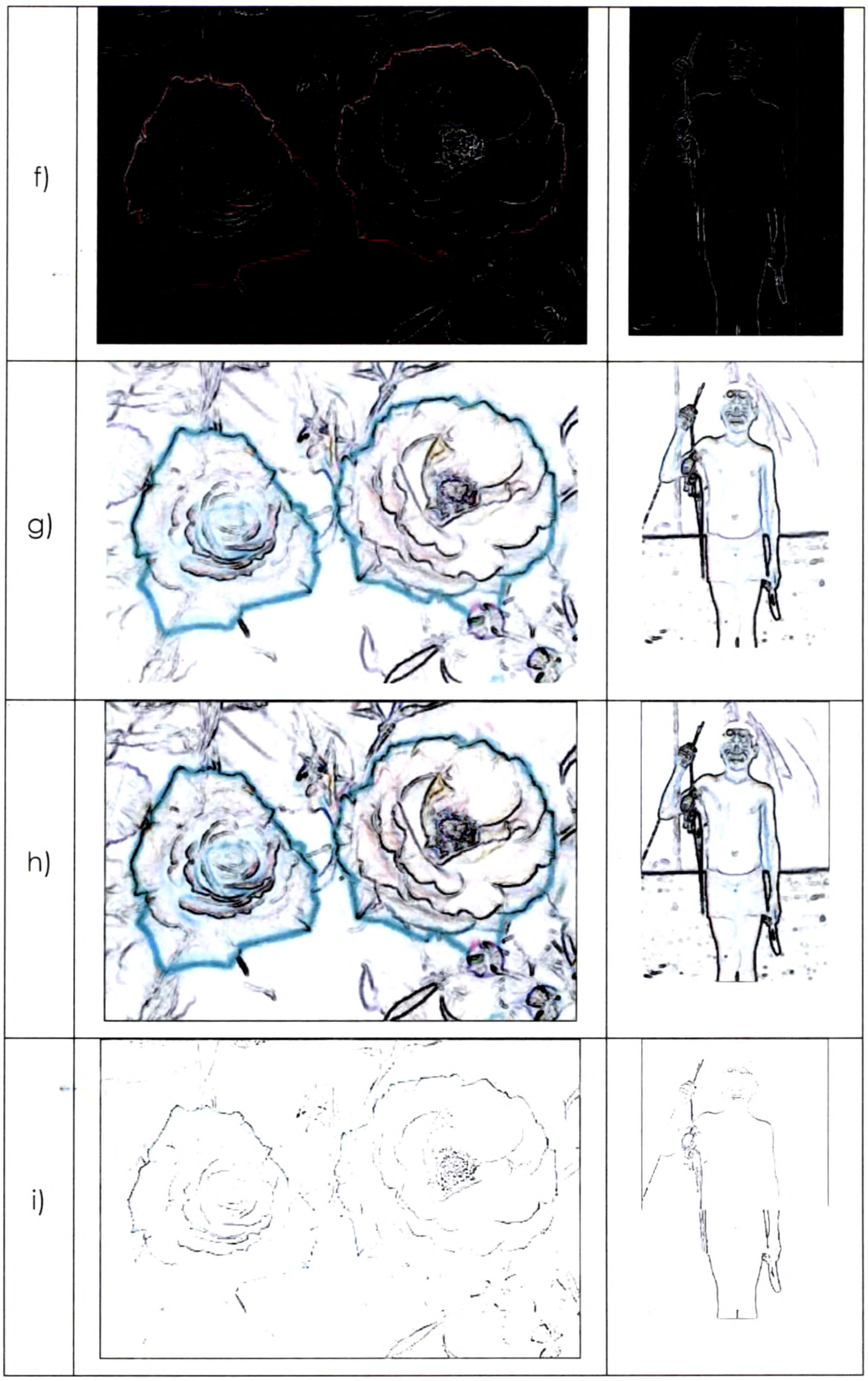

Figure 19 (Contd.). Edge Response Comparison. (f) Edge detection with ACD Photo Editor. (g) Edge detection with Adobe Photoshop. (h) Thick Edge detection with MS Photo Editor. (i) Thin Edge detection with MS Photo Editor.

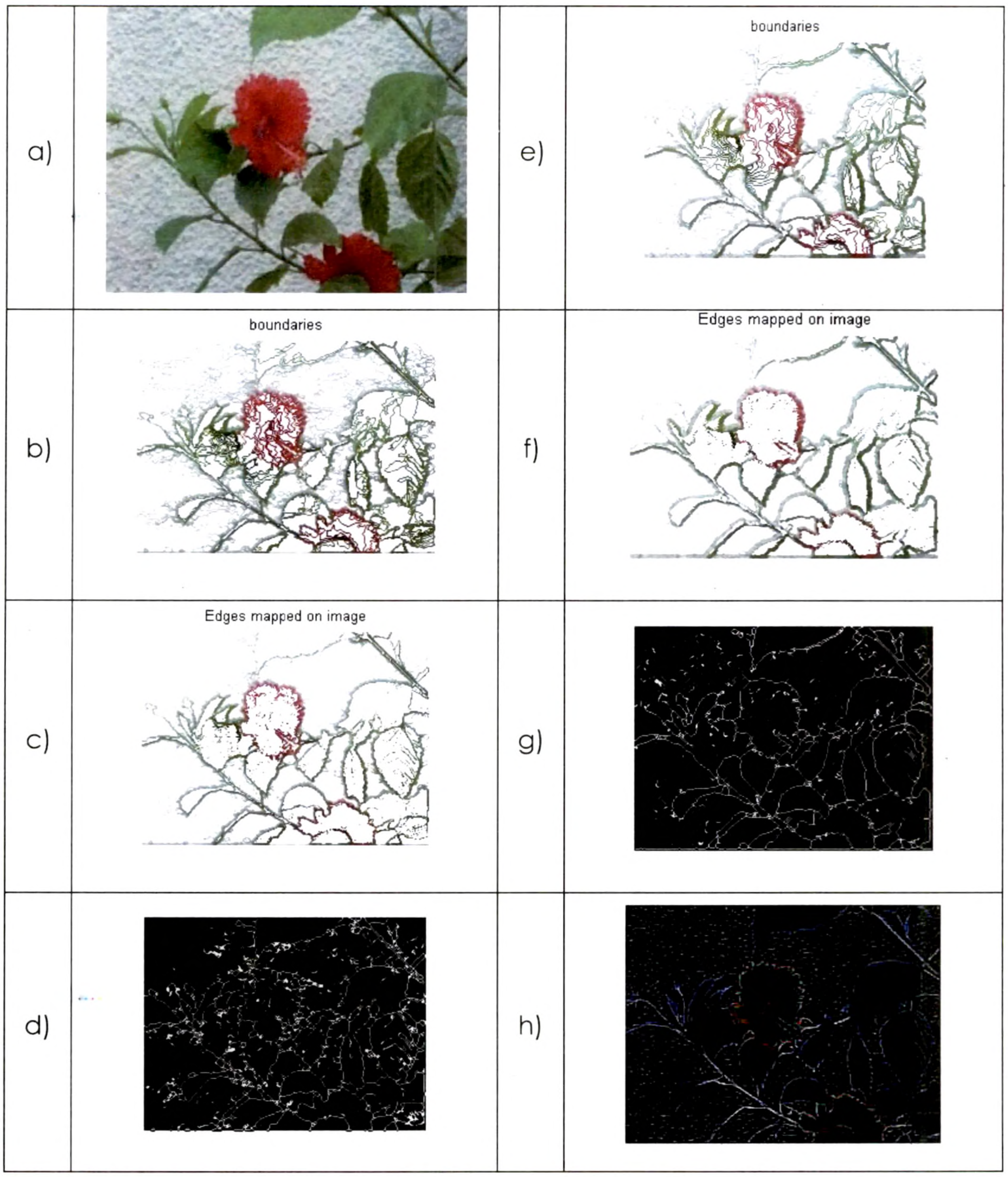

Figure 20. Edge Response Comparison. (a) Original image. (b) Candidate boundaries incorporating stationary Haar decomposition at level 1. (c) Detected edges from (b). (d) Thinned edges corresponding to (c). (e) Candidate boundaries incorporating stationary Haar decomposition at level 2. (f) Detected edges from (e). (g) Thinned edges corresponding to (f). (h) Edge detection with ACD Editor.

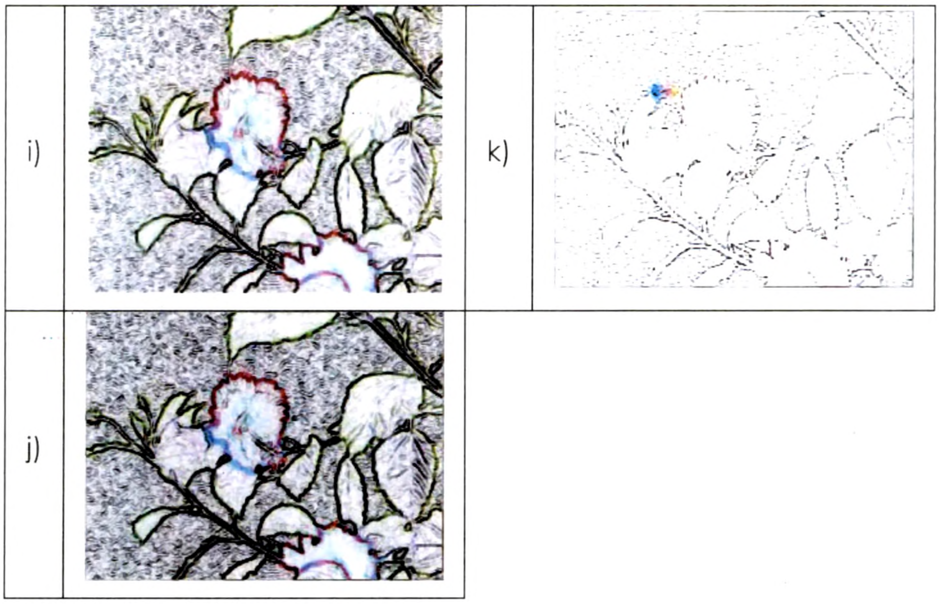

Figure 20 (Contd.). Edge Response Comparison. (i) Edge detection with Adobe Photoshop. (j) Thick Edge detection with MS Photo Editor. (k) Thin Edge detection with MS Photo Editor.

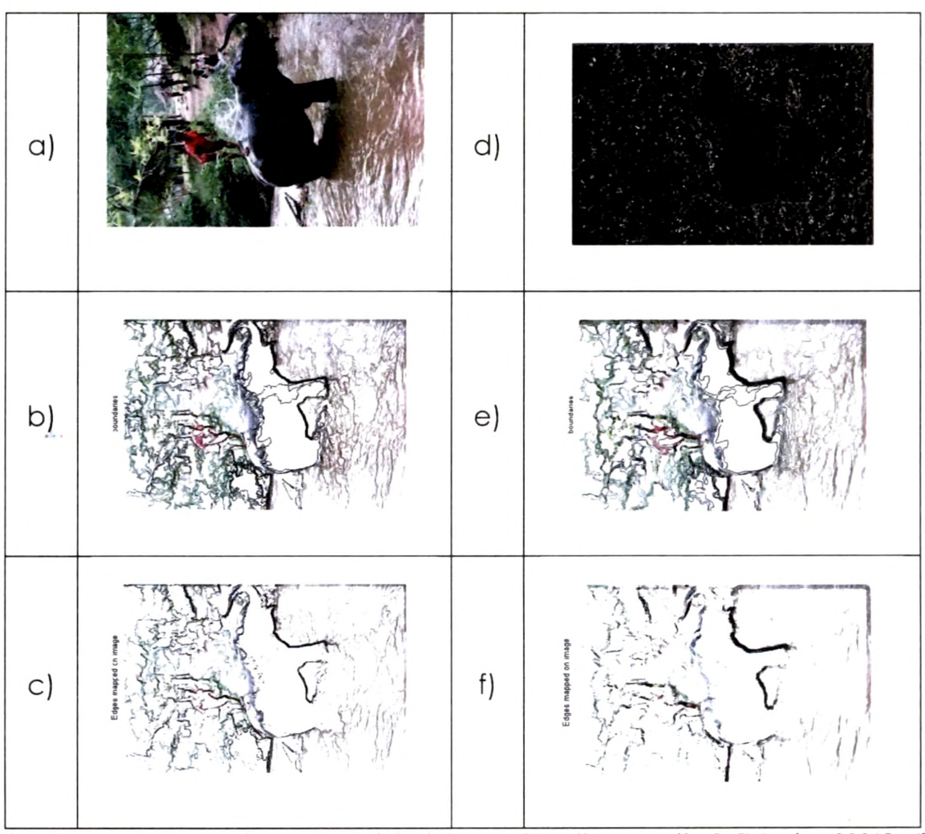

Figure 21. Edge Response Comparison. (a) Original image [Fowlkes, on line] [Martin, 2001]. (b) Candidate boundaries incorporating stationary Haar decomposition at level 2. (c) Detected edges from (b). (d) Thinned edges corresponding to (c). (e) Candidate boundaries incorporating stationary Haar decomposition at level 3. (f) Detected edges from (e).

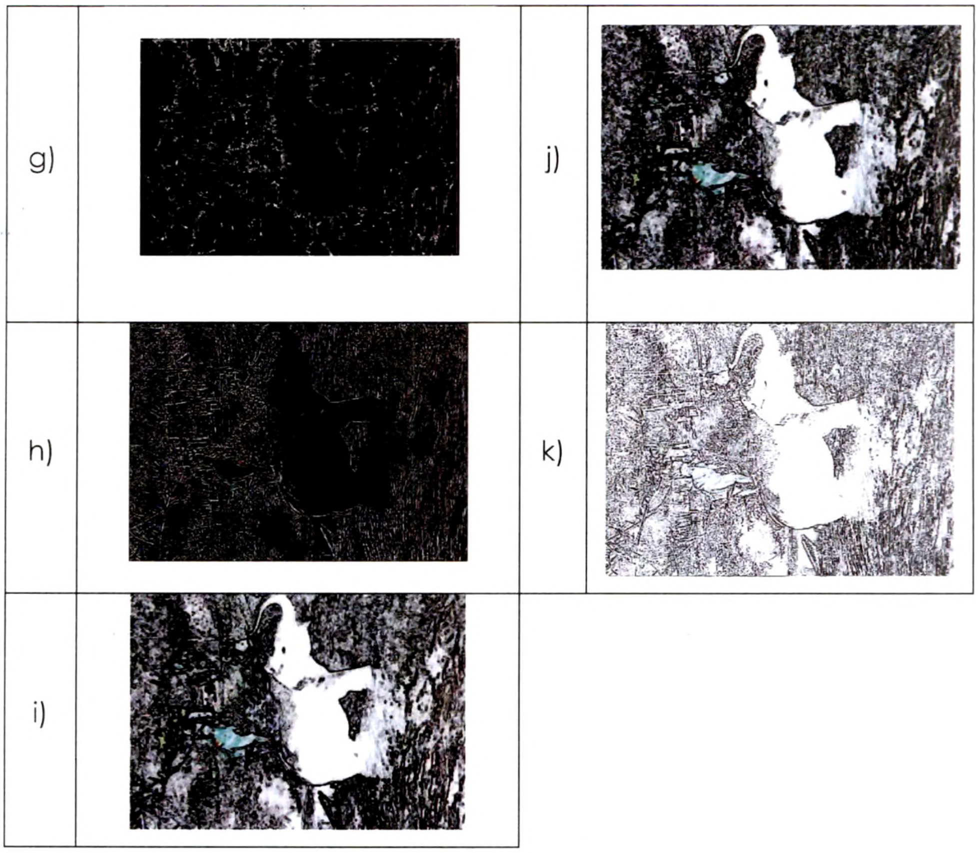

Figure 21 (Contd.). Edge Response Comparison. (g) Thinned edges corresponding to (f). (h) Edge detection with ACD Editor. (i) Edge detection with Adobe Photoshop. (j) Thick Edge detection with MS Photo Editor. (k) Thin Edge detection with MS Photo Editor.

4.3.4 Discussion

- The edge detection method based on candidate boundaries and proximity influence of all four channels detects perceptually significant edges, which are well localized and delineated.
- The detected edges are not necessarily thinned. The morphological operations are incorporated to produce thinned edges of one pixel width.
- The edges mapped on the image and thinned edges incorporating different levels of Haar wavelet decompositions are suitable as inputs to contour-detectors for producing continuity preserving closed contours and regions.
- The edge features may be used to derive shape features of objects.

- The method is well-suited for hierarchical multi-resolution approach for edge detection leading to image segmentation and object detection & identification for image content analysis and content based image retrieval.
- The selection of decomposition level of SWT decides the characteristics of the significant edges to be detected for meeting requirements of different categories of images, showing its versatility for applications.
- The detected edges and thin-edges can be incorporated to further reduce over-segmentation produced in prominent boundaries detected images, cited as future enhancement of the proposed work.
- The edge detection response analysis of the proposed method, ACD Photo Editor, MS Photo Editor and Adobe Photoshop was carried out on data set consisting of more than 300 images of different categories, resolutions and characteristics.
- The professional software packages are enough-sensitive (or over sensitive?) to detect edges constituted due to abrupt changes in color channels / textures. The sensitivity results into detection of a large number of edges, of them, many may not be visually significant. The algorithms for linking and processing of these large numbers of edges for contour generation / boundary detection / image segmentation may be not only complex but also computationally expensive.
- The results of the proposed method outperform others for i) detection of significant perceptual edges ii) elimination of insignificant edges corresponding background and foreground textures iii) better preservation of continuity.
- Quantitative analysis for comparison of edge responses of ACD Photo editor, Adobe Photoshop & MS Photo editor with proposed technique is presented in Annexure 4 showing better F – measure for proposed method.

4.4 Prominent Boundaries Detection

Image segmentation is a process of grouping region-forming pixels, satisfying single or multiple constraints on various direct or inferred cues of image attributes. Automatic segmentation of images is not only a crucial but also a challenging task. The precision-recall measures of the image segments significantly reflect the overall performance of image processing and computer vision applications involving postsegmentation phases. Any segmentation algorithm faces the biggest challenge of avoiding over and under segmentation – subjective and image category dependent criterions. Variety of image categories, variations in required segmentation-scales, vast variations of inter & intra object textures, multiple and occluded objects, changes in the inter region illumination conditions and different image resolutions make automatic image segmentation a difficult challenge. Hence, user specified parameters, user interactions or parameters tuning are generally inevitable for better performance of any algorithm capable of segmenting variety of images.

The bottom-up segmentation approaches rely on pixel level cues or inferred cues for forming and then merging regions. So, any mistake committed at low level processing of cues, propagates without giving chance for correction, imposing stringent demand on reliability of low level cues processing mechanisms [Kass, 1988]. Similarly, as hinted in [Arbel´aez, 2009], over segmentation is a common problem across feature clustering based approaches and lack of mechanism for enforcing contour closures may cause under segmentation resulted by joining regions of leaky contours.

The proposed novel method categorizes candidate boundaries into visually-prominent and non-prominent boundaries, considering local intensity cues of multiple color channels and pixel-prominence-values measured as a function of proximity-influence. The results of the method with and without incorporating a wavelet transform are compared for images of different characteristics, types and resolutions. The method has been exhaustively tested on textured, medical, natural, biometric and synthesized images for prominent boundaries detection and the results are qualitatively compared with those of human segmented images of benchmark image-segmentation dataset. The results presented show suitability and compatibility of the method for detecting prominent boundaries in various images. These boundaries - forming regions, make the basis for object detection and identification.

The proposed bottom-up approach for prominent boundaries detection with reliable processing of low level cues that preserves non-prominent boundaries. The approach emphasizes continuity preservation and minimizes chances of contours being leaky. The separation of non-prominent boundaries eliminates visually insignificant details as far as the segmentation is concerned. Preserved non-prominent boundaries may be used for corrections of mistakes and for a multi-scale hierarchical approach of automatic image segmentation.

4.4.1 The Method

The proposed method works on RGB color model and produces prominent and non-prominent contours by classifying candidate boundaries for all three color & gray channels. Refer to Figure 14 for the block diagram. The steps of the proposed methods are as follows:

Step 1: Detect Candidate boundaries and prominence measures, as described in edge detection method proposed in Algorithm 1, Section 4.3.1.

(Step 1 to Step 10 of Algorithm 1.)

Step 2: For all candidate boundaries C'_{ck} (of all four channels),

Compute number_of_prominent_vertices and total_vertices

Compute ratio = number_of_prominent_vertices / total_vertices

A vertex is called prominent-vertex if prominence_measure at the corresponding image coordinates is greater than threshold. The subscript c of C'_{ck} stands for the color channel under consideration and subscript k indicates contour identification number.

Step 3: Apply a classifier function λ to mark and separate prominent contours.

λ classifies contours based on contour length and ratio.

If ratio computed in above step is greater than 0.5 and a contour consists of more than 5 vertices (length), mark the contour as prominent and otherwise as non-prominent. Let P_c and N_c be a set of prominent and non-prominent contours respectively, containing classified contours.

Algorithm 2. Prominent boundaries detection.

The feature-preserving non-prominent boundaries are maintained in N_c is a salient characteristic of the method. Though N_c is not utilized at present, its usage may be explored.

The Figure 22 shows separated prominent and non-prominent boundaries for all color channels. As observed, the contribution of different color channels for constituting real, prominent boundaries is not homogeneous. Processing of any one channel may not detect a portion of real boundaries leading to under-segmentation of the image. The method not only provides reliable processing, but also takes advantage of redundancy of cues for precise, well localized detection of prominent boundaries.

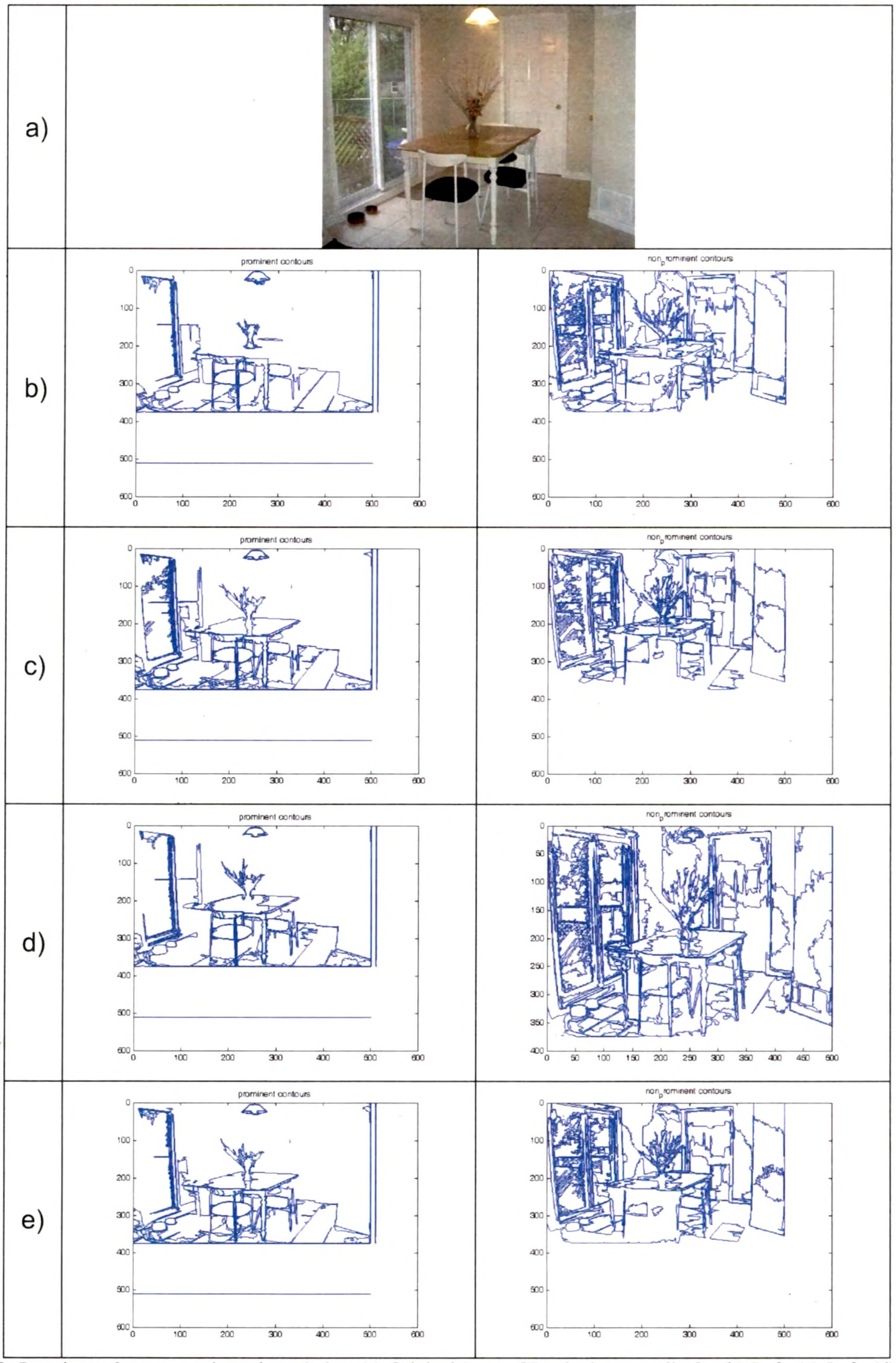

Figure 22. Prominent & non-prominent boundaries. (a) Original Image [Everingham, on line]. (b) Left, (c) Left, (d) Left, (e) Left: prominent boundaries of Red, Green, Blue and Gray channels respectively. (b) Right, (c) Right, (d) Right, (e) Right: non-prominent boundaries of Red, Green, Blue and Gray channels respectively.

4.4.2 Results

The salient characteristics of some of the images of test-set are tabulated below.

Table 3. Categorical Representative Test Images & Characteristics.

Description and salient characteristics of images	
Figure 23, left	The BSDB test image [Fowlkes, on line] [Martin, 2001], multiple objects, textured background, natural image.
Figure 23, right	The BSDB test image [Fowlkes, on line] [Martin, 2001], multiple objects covering significant portion of the image, objects touching image boundaries, natural image.
Figure 24, left	A standard test image.
Figure 24, right	The BSDB test image [Fowlkes, on line] [Martin, 2001], single central main object, captured with background softening filter, homogeneous background.
Figure 25, left	A synthesized image, smooth variations of color tones, light reflections and alphabets of typical colors & type on typical background.
Figure 25, middle	A close-up, resized to $1/8^{th}$ of original, image captured with high resolution device having inbuilt image processor.
Figure 25, right	Single central main object [Wang, 2001] [SIMPLIcity, on line], typical background.
Figure 26, left	An image of regular, repeated shapes [Wang, 2001] [SIMPLIcity, on line].
Figure 26, right	A biometric image - a finger-print.
Figure 27, left	The BSDB test image [Fowlkes, on line] [Martin, 2001], multiple similar objects, occluded objects in the object group, partially textured background, natural image.
Figure 27, right	An image of man-made object [Wang, 2001] [SIMPLIcity, on line].
Figure 28 left, right	The BSDB test images [Fowlkes, on line] [Martin, 2001].
Figure 29 left, right	The PASCAL challenge, 2008, images [Everingham, on line].
Figure 30, left	A medical image with less prominent boundaries [MedPics, on line].
Figure 30, right	The BSDB test image [Fowlkes, on line] [Martin, 2001], single central main object, reflections & whirls in the water.

The prominent boundaries and non-prominent boundaries of gray channel, mapped on images are presented here in Figure 23 to Figure 30 for various categorical test images for the qualitative comparisons of detected prominent boundaries with those of human segmented images of BSDB [Fowlkes, on line] [Martin, 2001]. The prominent boundaries detection results with Stationary Haar wavelet decomposition at various levels are shown for the comparison. Figure 28 (c) shows detected prominent boundaries without incorporating Stationary Haar wavelet decomposition.

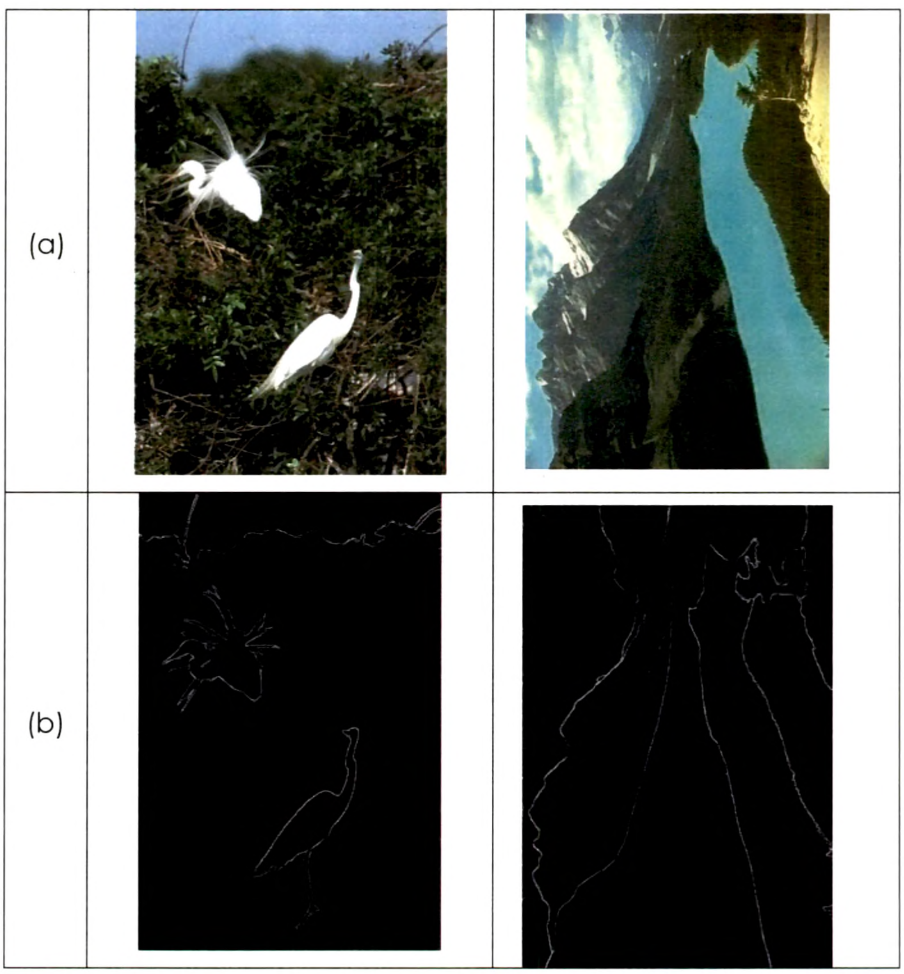

Figure 23. Comparison of human segmented image results with detected prominent boundaries. (a) Original image BSDB [Fowlkes, on line] [Martin, 2001]. (b) Human segmented image BSDB [Fowlkes, on line] [Martin, 2001].

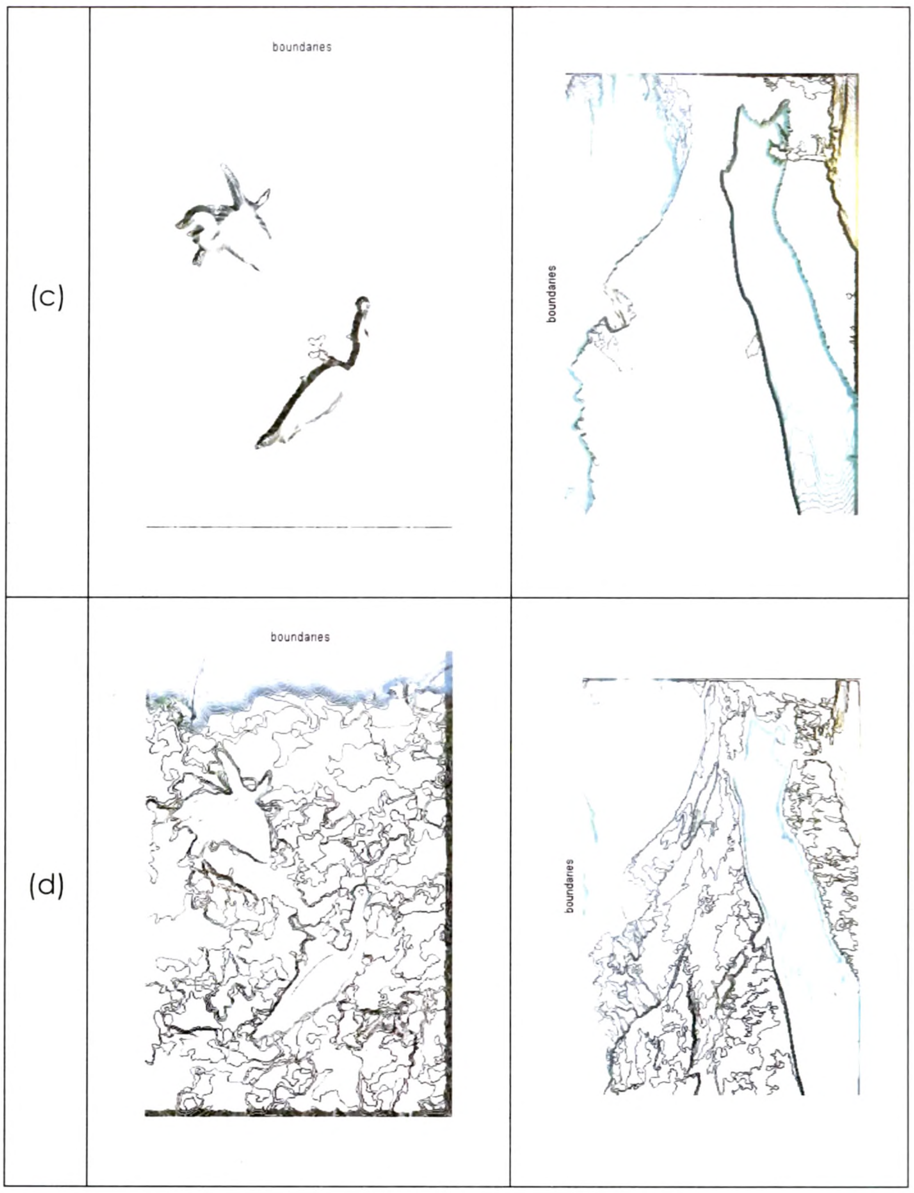

Figure 23 (Contd.). Comparison of human segmented image results with detected prominent boundaries. (c) Prominent boundaries incorporating Stationary Haar decomposition at level 2. (d) Non-prominent boundaries.

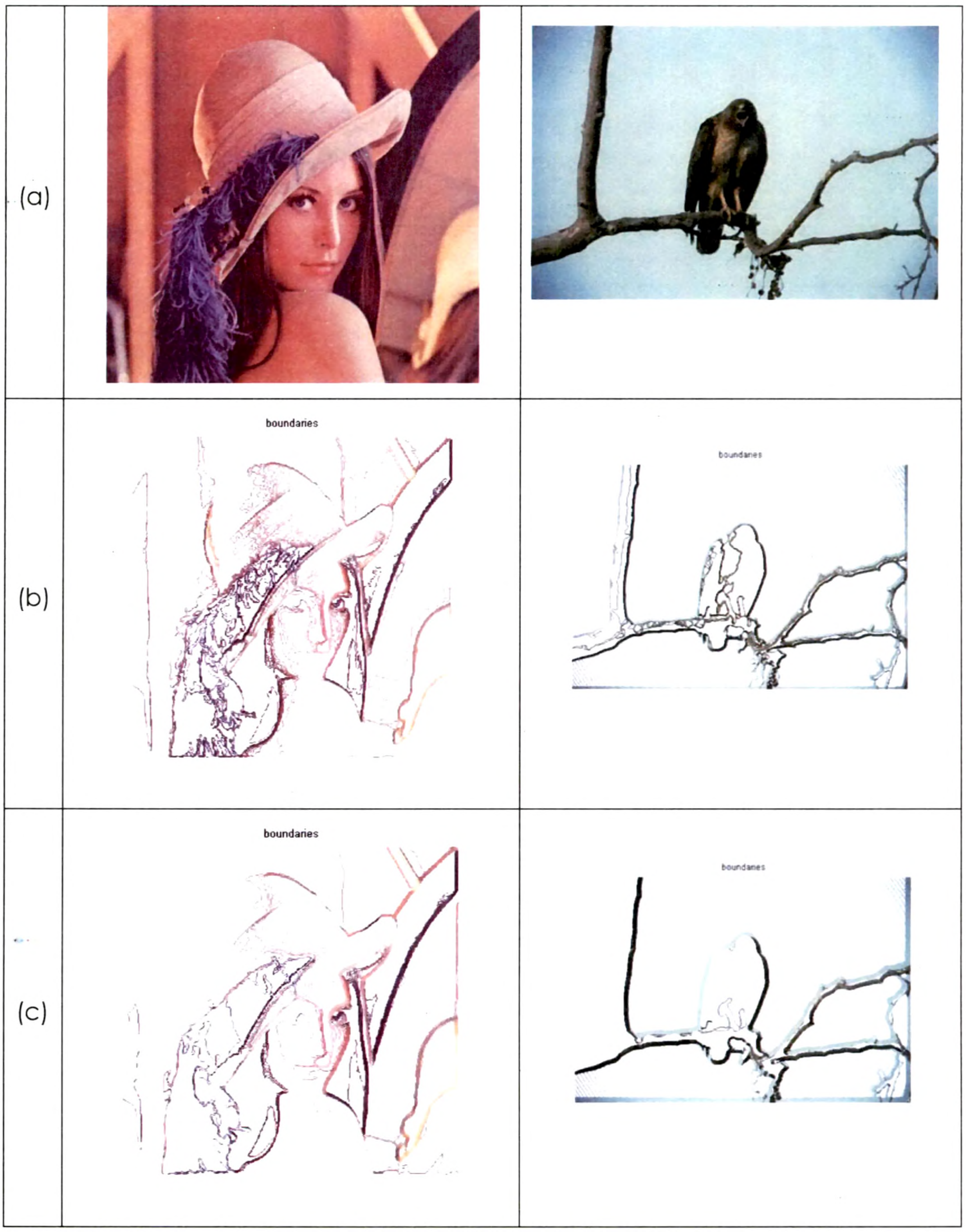

Figure 24. Prominent boundaries detection, incorporating different levels of Stationary Haar decompositions. (a) Left - Original image. (a) Right - Original Image BSDB [Fowlkes, on line] [Martin, 2001]. (b) Prominent boundaries incorporating Stationary Haar decomposition at level 2. (c) Prominent boundaries incorporating Stationary Haar decomposition at level 3.

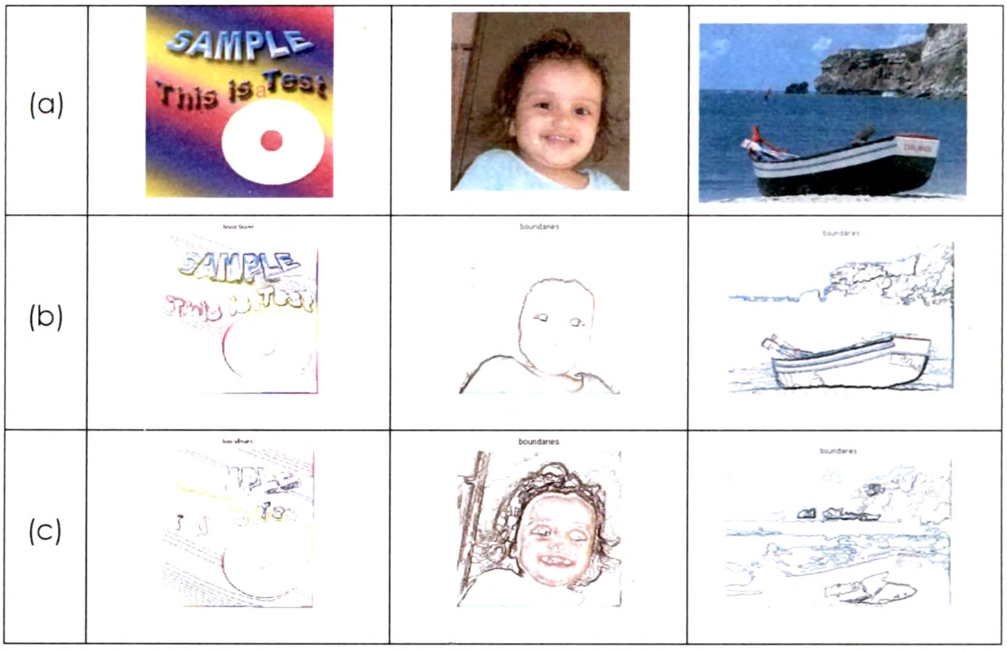

Figure 25. Prominent boundaries detection results - Different categorical images. (a) Left & Middle - Original images. (a) Right - Original image [Wang, 2001] [SIMPLIcity, on line]. (b) Prominent boundaries incorporating Stationary Haar decomposition at level 2. (c) Non-prominent boundaries.

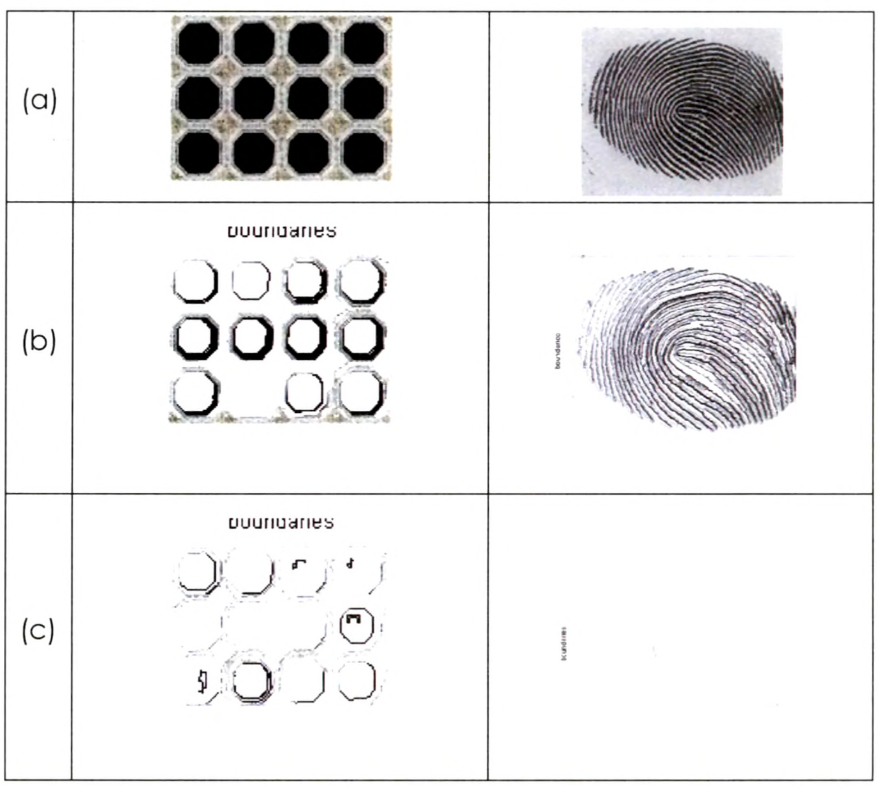

Figure 26. Prominent boundaries detection results - Different categorical images. (a) Left - Original image [Wang, 2001] [SIMPLIcity, on line]. (a) Right - Original image. (b) Prominent boundaries incorporating Stationary Haar decomposition at level 2. (c) Non-prominent boundaries.

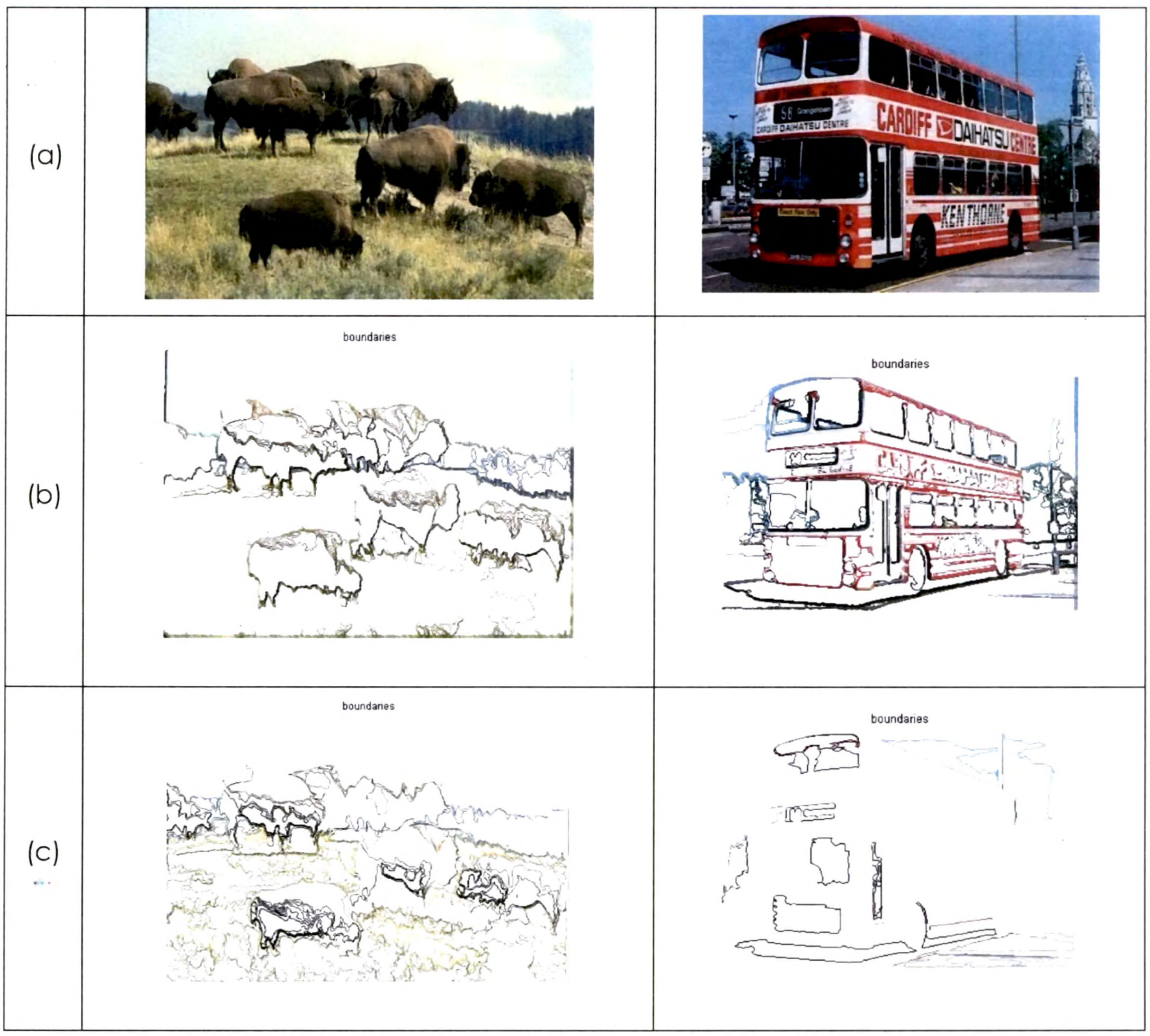

Figure 27. Prominent boundaries detection results - Different categorical images. (a) Left - Original image [Fowlkes, on line] [Martin, 2001]. (a) Right - Original image [Wang, 2001] [SIMPLIcity, on line]. (b) Prominent boundaries incorporating Stationary Haar decomposition at level 2. (c) Non-prominent boundaries.

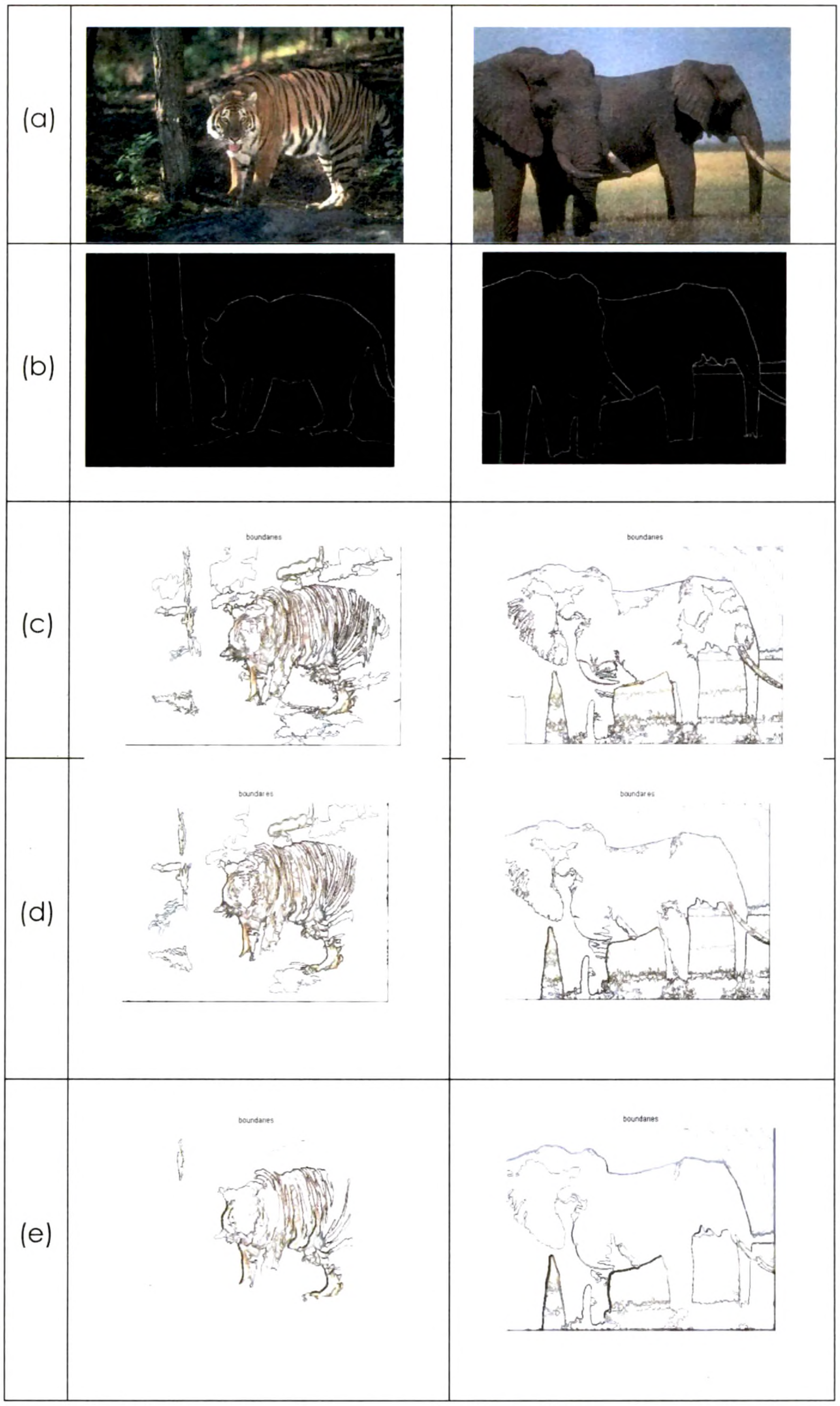

Figure 28. Comparison of human segmented image results with detected prominent boundaries. (a) Original image BSDB [Fowlkes, on line] [Martin, 2001]. (b) Human segmented image BSDB [Fowlkes, on line] [Martin, 2001]. (c) Prominent boundaries without incorporating Stationary Haar decomposition. (d) Prominent boundaries incorporating Stationary Haar decomposition at level 1. (e) Prominent boundaries incorporating Stationary Haar decomposition at level 2.

Figure 29. Prominent boundaries detection results - Different categorical images of PASCAL challenge 2008. (a) Original images [Everingham, on line]. (b) Prominent boundaries incorporating Stationary Haar decomposition at level 1. (c) Non-prominent boundaries.

Figure 30. Prominent boundaries detection results - Different categorical images. (a) Left - Original image [MedPics, on line]. (a) Right - Original image BSDB [Fowlkes, on line] [Martin, 2001]. (b) Detected prominent boundaries incorporating Stationary Haar decomposition at level 1. (c) Non-prominent boundaries.

4.4.3 Discussion

- The detected prominent boundaries are well-localized and well-delineated.
- The processing of low level cues generating multiple candidate boundaries enforces reliability for categorizing prominent boundaries with continuity preservation.
- Categorization resulting into exclusion of non-prominent boundaries separates insignificant features from significant ones (from segmentation point-of-view).
- The Stationary Haar wavelet decomposition and detected prominent boundaries at various levels make the approach suitable for multi-scale hierarchical image segmentation.

- The method produces significantly comparable results for a test-set consisting of more than 300 images, covering representative images of different categories, possessing performance challenging, wide variety of salient characteristics (as presented in Table 3).
- The prominent boundaries detection results are effective for Berkeley Segmentation Dataset images [Fowlkes, on line] [Martin, 2001], PASCAL challenge 2008 database images [Everingham, on line] and SIMPLIcity database images [Wang, 2001] [SIMPLIcity, on line].
- The development of effective methodology for identifying regions pertaining to objects make the proposed wavelet based hierarchical method suitable for applications like object detection, object identification, automatic image tagging, content based image retrieval and visual scene analysis.

4.5 Concluding Remark

The continuity preserving well localized prominent boundaries form the basis for segmentation, feature extraction and foreground separation for CBIR ...