Chapter 4

RGBD Complex salient object detection with improved probabilistic contrast and global concave topographical saliency

The salient object detection inspired by the human attention mechanism. Most of the saliency methods generate prominent objects from 2D information, while human attention systems are 3D perception mechanisms. In this chapter, additional depth information from RGBD is utilized to robustly and correctly detect the salient object in a complex and clutter background. To distinguish the salient object in complex and clutter background, the saliency of object border increases in Poisson probabilistic contrast space. This process produces a global concave reference surface. The intra-regional spatial, structural, color, and depth information is integrated into this global reference plain to detect the salient object correctly. Additional, Background estimation and central saliency integration will thoroughly remove the background. This algorithm generates a robust conspicuous object. The detail introduction of 3D saliency and related methods is properly discussed in next section 4.1.

4.1 Introduction

Recently, visual saliency has been defined as highlighting a most prominent object from cluttered and complex backgrounds. Initially, the problem of saliency originated from neuroscience, psychology, and computer vision applications. Later salient object detection attracts the researcher's interest in computer vision and image processing domains to predict the complete salient object. It has recently witnessed significant advancement in the saliency computation model to predict the salient object accurately. There are various saliency computation models reported in the literature. These models have a significant contribution to adhere to some contribution toward accuracy and robustness. In these models, global prior, central prior, background prior, connectivity prior, and depth prior is the most reported features to enhance the saliency computation. Most contemporary-based methods simply add the various saliency features, which leads to inaccurate and inconsistent predictions of salient objects. In contrast, GCS is used as a global concave reference surface in the proposed model, approximately containing the salient object. This reference surface has distinguishing characteristics.

The computational model of saliency is mainly categorized into three domains. The initial computational model is based on bottom-up, low-level feature-based and starting from an image without training and learning. And the most dominating feature in salient object detection in this model is contrast defined as pixel-level contrast [35], region-level contrast [62], multi-scale contrast [13], center-surround contrast [11] color contrast, and spatial contrast, etc. Although other highly reported features in recent literature are center prior [40], and background connectivity [12] [41], surroundness [36], depth [43] and abjectness [44]. The second computational model is top-down learning-based and dependent on high level semantic [18], contextual [91] and structural features [149]. These features are using in training and learning with manually annotated ground truth data. The recent computation model is a hybrid model that integrated the low level and high-level features. Most of the model varies on proposing the integration strategies to increase the robustness in saliency detection.

In particular, we define three challenges in the model of saliency computation: (1) Interior saliency discrepancy (2) exterior saliency discrepancy, and (3) object border discrepancy. Next, we discuss these challenges and our motivation to mitigate these challenges in holistic based approaches. Interior saliency discrepancy is defined as “removing the saliency of the salient region, which are similar to background regions.” Exterior saliency discrepancy is explained as “increasing the saliency of non-salient regions which are similar to salient object regions.” Object border discrepancy is defined as destroying the structure of the object border regions.

The global contrast and other low-level features based saliency models [11], [66], [4], [5],etc, are computationally efficient and produce full-length saliency. While this model generates interior, exterior border region saliency discrepancies. Most of the models are failed in complex and clutter background. The central saliency based on cellular automata is optimal and highly referenced reported in literature, which minimized the interior saliency. In contrast, these models produce exterior as well as border region discrepancy. Therefore, this model is used in the saliency enhancement stage in the proposed method. Some other recent saliency models measure the backgrounds to remove the exterior saliency discrepancy. These approaches minimized the exterior saliency while it has not reduced the interior as well as border saliencies discrepancies. These entire 2-D models are failed in low depth images. The depth clues in RGBD saliency provides an additional space to increase the saliency in low depth 3D images and it have discriminative power against the complex and clutter background. Therefore, to capture the low depth features RGBD saliency model is used. RGBD saliency model capture low level depth information while itself not sufficient for salient object detection. Therefore, Cheng.et.al [43] used color and structural based regional saliencies for saliency. But this model produces saliency which minimized exterior saliency and improved the interior saliency but failed on

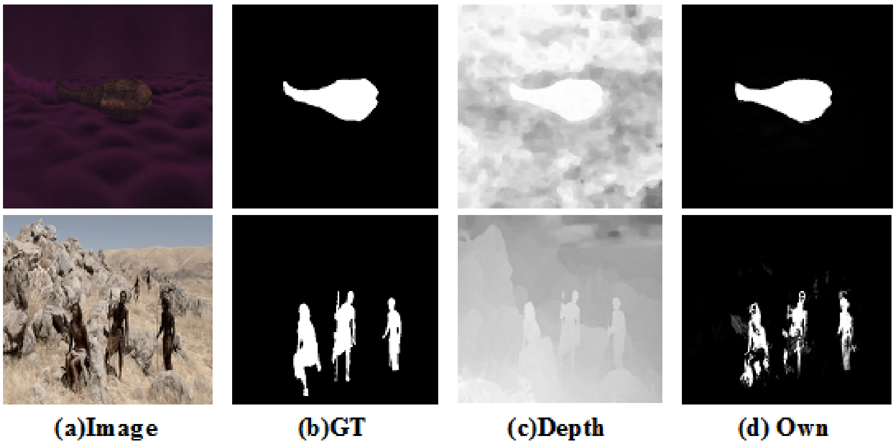

FIGURE 4.1: Saliency detection in complex and clutter background with minimize discrepancies in interior, exterior and border regions saliency.

border region discrepancy. Zhu. et. al [38] used dark channel, central channel and other purifying saliency feature along with depth features. This model produce better saliency than other RGBD model. This model is minimized both interior as well as exterior saliency although this model is failed in border region discrepancy.

Targeting to address the aforementioned limitations of saliency computation models on challenging datasets with complex and clutter background, the proposed method generate the global concave topographical saliency-GCS. This surface used as a reference surface for minimizing all these said discrepancies. The global concave based saliency is vital in providing reference plain for regional saliencies integration. Because this reference surface have enhanced saliency on object boundary through the DoG based contour. This enhanced boundary with improved probabilistic contrast preserves the border regions saliency during regional saliency integration and proven through result as discriminating characteristics. This novelty have added a different space attention rule for salient object detection.

To overcome the limitation of low depth in challenging scenarios and complex images having depth features are used recently to improve the saliency computations. Cheng *et al.* [43] compute saliency by using both color and depth features. Peng *et al.* [98] used a fusion framework that combines depth-based saliency with RGB-based saliency. Geng *et al.* [97] proposed the salient object detection in the stereo images based on depth-based saliency. Recently depth cue is combined by Zhu *et al.* [38] with regional saliency, dark saliency, and center saliencies. In this method, the author used the dark channels prior, center, and depth to increase the robustness. The results of depth saliency are a valuable consideration compared to previous visual saliency work in increasing the robustness of saliency computation.

Aiming these limitations of global, regional as well as background prior based methods motivate to proposed a global concave topographical reference surface. This surface increase saliency in border regions. The intra- regional distance-based saliency and spatially weighted saliency are integrated into the Global reference surface to increase the interior saliency. The regional color saliency, depth saliency are integrated using Gaussian function into a well-defined global reference plane to enhance the object's interior region saliency and minimized the exterior saliency. Further integration of the center saliency has uniformly removed the background and highlights the prominent object in complex and challenging images.The main contributions of the proposed method for aiming the above mentioned discrepancies as follow:

- In this method, a novel global concave reference surface GCS is proposed by addition of DoG based contour and improved probabilistic contrast based saliency to minimized the border region discrepancies.

- To the best of our knowledge, we are proposing for the first-time global concave saliency based reference plain in RGBD saliency computation.
- The integration of spatial, regional, color and depth saliencies into global concave reference surface to minimized the interior saliency discrepancy.
- The integration of spatial, regional, color and depth saliencies into Gaussian based background elimination model to minimized exterior saliency.

The rest of the sections of this chapter is organized in three sections. In the next section, 4.2, the proposed method is adequately defined and explained. The experiments and result analysis with state-of-the-art methods are demonstrated in the section , 4.3. The conclusion and future scope is presents in fifth section 4.4.

4.2 The proposed method

4.2.1 Initialization through global concave surface (GCS)

The global concave surface is used to initialize saliency computation. This surface is composed of Improved Poisson Probabilistic Contrast-IPC and DoG based contour enhanced global surface. The overview and complete block diagram of proposed models is shown in Fig.4.2

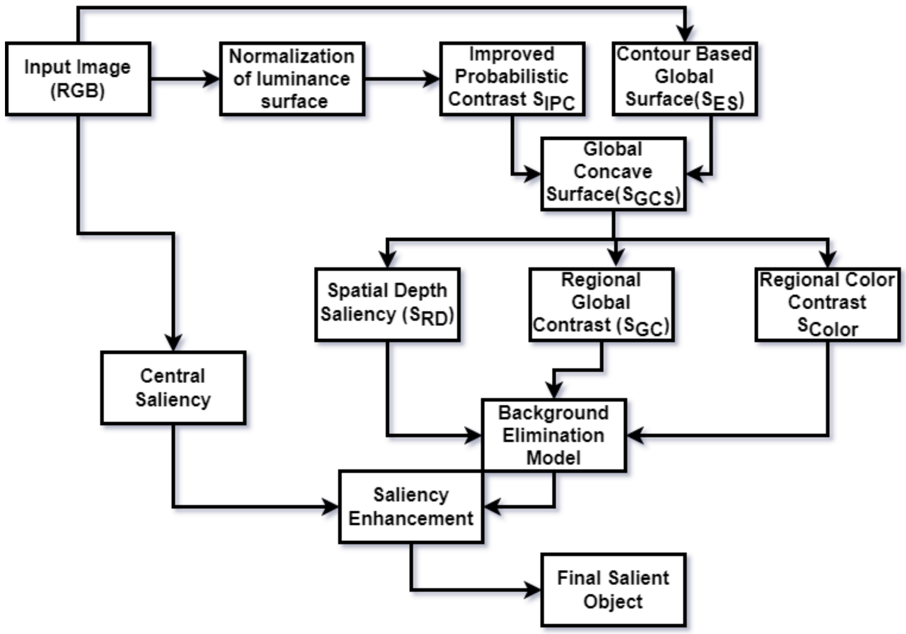

FIGURE 4.2: Block diagram of proposed Improved Probabilistic Model.

4.2.1.1 Improved Poisson probabilistic contrast (IPC)

Poisson Probabilistic modeling is used as *pdf* of the image planes. This *pdf* is used to compute the probabilistic contrast. Generalized Poisson distribution is the better choice because it has characteristics of convergence of information divergence into a concave shape topographical surface. The probabilistic distribution ϕ for each color channel $c = [l, a, b]$ in CIE-LAB space for input original image I_0 with mean μ is defined as:

$$\phi^c(I_0, \mu) = \frac{e^{-\mu}\mu^{I^c}}{I^c!} \tag{4.1}$$

The Improved Poisson Probabilistic Contrast-IPC is addition of contour enhanced global surface with Poisson Probabilistic Contrast [175]. It is Poisson based global contrast with normalized likelihood surround symmetry. The Improved Poisson Probabilistic Contrast-IPC is formulated using color chrominance channel $c = [a, b]$ and luminance channel l in $CIE - LAB$ space for input image I_0 . It is defined as follows:

$$S_{IPC} = \sum_{c \in a,b} \underbrace{\|I_0^c - \phi^c I_0^c\|}_{ChrominanceContrast} + \underbrace{\left\|I_0^l - \phi^l I_0^l\right\|}_{LuminanceContrast} N_{Coff} \tag{4.2}$$

Where N_{Coff} is called normalization coefficient. This coefficient is used to normalize the Poisson probabilistic luminance contrast. It is defined as:

$$N_{Coff} = \left(\frac{1}{2}p_k^2 + \frac{1}{6}p_k^3 + \frac{1}{3}p_k^4\right) * \gamma \tag{4.3}$$

where $\gamma = \sqrt{R_\sigma} - \sqrt{R_\mu}$ is measures the divergence effect of uneven luminance into image-planes chrominance. R_σ is relative contrast of variance between luminance plain and chrominance plain. R_μ is relative contrast of mean between luminance to chrominance mean of image plain. P_k is the k^{th} point probability in Poisson probabilistic space. N_{Coff} is visualized as the region of uneven distribution of luminance.

4.2.1.2 Contour based global surface

The DoG filter is efficiently approximates the Laplacian of Gaussian. This edge detection method are widely reported in literature [176]. The global concave topographical surface is computed by addition of contour based global surface, generated by Difference of Gaussian $DoG(x, y)$ of the input image $I_0(x, y)$, as defined in Eq.

4.4, 5.4. Here, σ_1 and σ_2 are the standard deviation,where $\sigma_1 > \sigma_2$. The $DoG(x, y)$ is defined as follow:

$$\begin{aligned} DoG\left(x,y\right) &= \frac{1}{2\pi}\left[\frac{1}{\sigma_1^2}e^{-\frac{(x^2+y^2)}{2\sigma^2}} - \frac{1}{\sigma_2^2}e^{-\frac{(x^2+y^2)}{2\sigma^2}}\right] \\ &= G(x,y,\sigma_1) - G(x,y,\sigma_2) \end{aligned} \tag{4.4}$$

This contour surface is generated by integration of multiple edges. Let we define the range of these edges as $\varphi = \sigma_1/\sigma_2$. So all the edges over DoG with standard deviations in the ratio φ. It is defined as:

$$S_{ES} = \sum_{i=0}^{N-1} G\left(x, y, \varphi^{i+1}, \sigma\right) - G\left(x, y, \varphi^{i}, \sigma\right) \tag{4.5}$$

This S_{ES} surface integrates $N-1$ number of edge surface into the initial edge surface to enrich the boundary of the object. The initial GCS is a simple addition of edge enhanced global contour surface and enhanced Poisson probabilistic contrast surface. This surface has characteristics of enriched object boundary [176]. Therefore, it is used as reference plain for other saliencies integration and background removal. Which is defined as follow:

$$S_{GCS} = S_{IPC} + S_{ES} \tag{4.6}$$

4.2.2 Regional contrast integration into GCS

Initial GCS, global concave topographical saliency is used as a reference plane. It maximize the information of object while reduce the saliency of background regions.

4.2.2.1 Regional saliency integration with GCS

After global GCS computation, initial image plane I_0 is divided into K color-based regions by using the K-mean algorithm. The same regional descriptor is used for regional color, depth, and spatial saliency into GCS topographical saliency. Where spatial saliency SS_j is regional density, defined as a ratio between the pixel in region i and total pixels. The spatial depth saliency into depth I_d space is defined as follows:

$$S_{SD}(r_k) = \sum_{i=1, j\neq k}^{K} SS_i e^{\frac{Dis_0(r_k, r_i)}{\sigma^2}} Dis_d(r_k, r_i) \tag{4.7}$$

Where $Dis_d(r_k, r_i)$ is the Euclidean distance between region i with central region k in depth space. Similarly, regional color saliency in color space and regional probabilistic contrast saliency in GCS space is calculated as:

$$S_{color}(r_k) = \sum_{i=1, i\neq k}^{K} SS_i e^{\frac{Dis_0(r_k, r_i)}{\sigma^2}} Dis_{color}(r_k, r_i) \tag{4.8}$$

Where $Dis_0(r_k, r_j)$ is the spatial distance and saliency and σ is controlling parameter while $Dis_{color}(r_k, r_i)$ is regional color saliency based on the Euclidean distance between central region k^{th} and i^{th} region in $L*a*b$ color space.

$$S_{GC}(r_k) = \sum_{i=1, i\neq k}^{K} SS_i e^{\frac{Dis_0(r_k, r_i)}{\sigma^2}} Dis_{GCS}(r_k, r_i) \tag{4.9}$$

$Dis_d(r_k, r_i)$, $Dis_{color}(r_k, r_i)$ and $Dis_{GCS}(r_k, r_i)$ are depth, color, and probabilistic contrast based saliency respectively, which minimize the interior discrepancy with regional weighting parameter like SS_i and $Dis_0(r_k, r_j)$ $Dis_d(r_k, r_i)$, $Dis_{color}(r_k, r_i)$ and $Dis_{GCS}(r_k, r_i)$. This regional saliency integration into GCS space increase some non-salient points. This exterior saliency discrepancy is remove in Background estimation model.

4.2.2.2 Background estimation model

In the saliency computation domain, it is assumption of center prior and background prior hypothesis [43], that salient object is mostly located in the center of the image. So integrating factor of these regional saliencies is defined using the normalized Gaussian function. Let Pos_k and Pos_c represent the position of k^{th} region and central region respectively. N_k, denotes the number of pixels in k^{th} region. The weight-based integrating factor (WF_c) is calculated as:

$$WF_c(r_k) = \frac{Gaussian(Dis_d(Pos_k - Pos_c)}{N_k} GW(D_k) \tag{4.10}$$

In this equation, Dis_d is distance in Euclidean space and $GW(D_k)$ is depth weight, which is calculated as:

$$GW(D_k) = max(D - D_k)$$

1(max(D)-minD) (4.11)

Finally, Saliency is computed by integrating three regional saliencies, through normalized Gaussian function to reduce the interior saliency discrepancy, which is defined as:

$$S_G = Gaussian(S_{GD}(r_k) + S_{color}(r_k) + S_{GC}(r_k))WF_c \tag{4.12}$$

4.2.2.3 Saliency enhancement

The hypothesis of Biological plausible architecture [173] is described the phenomena of centralization of object always towards the center of the image. The center prior is also preferred because of the mindset characteristics of the photographer. Central bias preferred in saliency detection and enhancement. [174] [155]. Therefore, S_{cen} is used in saliency enhancement, which is based on the central saliency BSA [14] algorithm. This algorithm is used to remove the edge effect and minimize the exterior saliency discrepancy while enriching the interior saliency. Final saliency is the simple addition of central saliency S_{Cen} and S_G

$$S = (S_G + S_{Cen}) \tag{4.13}$$

4.2.3 Theoretic foundation

The normalization of luminance plain over chrominance plain in Poisson distribution is defined as maximum likelihood estimation. The measure of uneven distribution is defined in term of influence of region of surround symmetry. The characteristics of surround symmetry regions and its information divergence is proved, formulated and described by H.Perter [172]. In this method, the strict topographical concave surface lemma [172] is used as a theoretic principle for normilising the global probabilistic contrast. Suppose a pixel is having Poisson probability as p_i of a pixel i, it is the maximum-likelihood estimate of probability occurred around mean of the distribution [175]. Hence, the maximum bond of similarity of region or pixel's symmetric surround is approximated in terms of total variation in Poisson distribution. This normalized likelihood luminance plain is used to measure the global probabilistic contrast by subtracting the maximum likelihood from image plains in CIE-LAB space rather than mean of image plains.

Let us define the Poisson probability distribution $\phi(\mu)$ with mean μ. Let P and Q be probability measures on $\{0, 1, 2, 3...N\}$ with point probabilities as p_i and q_i in terms of pixel values in CIE-LAB color image where i= $\{0, 1, 2, 3...N\}$ and $N = 255$. Then the total variation between the distributions is defined as:

$$\|P - Q\| = \sum_{i=0}^{N} |p_i - q_i| \tag{4.14}$$

The divergence of information or region of similarity for creating the contrast is defined as:

$$D\,(P \parallel Q) = \sum_{i=0}^{N} p_i \log \frac{p_i}{q_i} \tag{4.15}$$

Lemma 4.1. *The bond of maximum divergence in total variation in Poisson distribution is used as normalization coefficient of luminance plain over chrominance plain.*

Proof. The bond of maximum divergence in total variation is defined as region of influence of uneven distribution of luminance over chrominance plains around the points in Poisson distribution space. Consider the $X_1, X_2, X_3....X_N$ is a sequence of image plains, defined as independent Bernoulli probabilistic distribution, where $P_k = P(X_k = 1)$ and $\mu = \sum^n p_k$.

$$\begin{aligned} D(X_k) &= (1-p_k)\,ln\left(\frac{1-p_k}{exp\,(-p_k)}\right) + p_k ln\left(\frac{1-p_k}{exp\,(-p_k)}\right) \\ &= (1-p_k)\,ln\,(1-p_k) + p_k \\ &\leqslant (1-p_k)\left(-p_k - \frac{p_k^2}{2} - \frac{p_k^3}{3}\right) + p_k \\ &= \left(\frac{1}{2}p_k^2 + \frac{1}{6}p_k^3 + \frac{1}{3}p_k^4\right) \end{aligned} \tag{4.16}$$

□

Other characteristics to measure the divergence of information in Poisson distribution is properly proofed and discussed in various lemma and theorem by H.Perter [172].

4.2.4 The proposed algorithm

The proposed method is summarized in the following algorithm. To simplify the proposed method, two algorithm are use to describe the sequential steps as follows.

Input : Input original image $I_0 = \{l, a, b\}$ in CIE-LAB color format. ϕ is Poisson based PDF, μ is mean of respective color plains σ is variance.

Output: Global concave topographical reference saliency surface S_{GCS}

Compute $\delta_a \leftarrow tan^{-1}(\sigma_a/\sigma_l)$

Compute $\delta_b \leftarrow tan^{-1}(\sigma_b/\sigma_l)$

Compute $\gamma \leftarrow \left|\sqrt{R_\sigma} - \sqrt{R_\mu}\right|$

Compute $p_k \leftarrow tan(45^0 - \delta_a)tan(45^0 - \delta_b)$ `// for` k^{th} `image`

Compute $N_{Coff} = \left(\frac{1}{2}p_k^2 + \frac{1}{6}p_k^3 + \frac{1}{3}p_k^4\right) * \gamma$

Compute $S_{IPC} \leftarrow \left(I_0^l - \phi^l I_0^l\right)^2 N_{Coff} + (I_0^a - \phi^a I_0^a)^2 + \left(I_0^b - \phi^b I_0^b\right)^2$

Compute $S_{ES} = \sum_{i=0}^{N-1} G\left(x, y, \varphi^{i+1}, \sigma\right) - G\left(x, y, \varphi^i, \sigma\right)$

Finally Compute $S_{GCS} \leftarrow S_{IPC} + S_{ES}$

Algorithm 5: To generate the global concave reference plain using improved Poisson based probabilistic contrast-IPC and Gaussian based Contour

Input : Input initial globle Concave saliency S_{GCS} and original input color image I_0into CIE-LAB space

Output: Final saliency S

for $k \leftarrow 1$ **to** K *color region* **do**

Compute the reginol depth saliency $S_{SD}(r_k)$ by Eq. 4.7

Compute the reginol color saliency $S_{Color}(r_k)$ by Eq.4.8

Compute the reginol spatial saliency $S_{GC}(r_k)$ by Eq.4.9

Compute the Reginol Gaussian background ellimination weight $WF_c(r_k)$ by Eq.4.10

Intregate all regional saliency

$S_G = Gaussian(S_{GD}(r_k) + S_{color}(r_k) + S_{GC}(r_k))WF_c$ by Eq.4.12

end

Compute the central saliency S_{Cen}

Compute final saliency $S \leftarrow (S_{Cen} + S_G)$ by Eq.4.13

Algorithm 6: Regional depth,color and spatial saliencies integration in global concave topographical saliency S_{GCS}

4.3 Experimental and Result Analysis

4.3.1 Data-Set

The proposed method is extensively evaluated on two publicly available complex datasets for salient object detection. The first dataset, RGBD-1000 [98], contains 1000 images, which contains the multifarious background, very similar to the salient object. Each image is having a resolution of 640×480. The second dataset is PKU-80 [38], which images have confusing backgrounds with a resolution of 960×1080. This dataset is designed with a complex scene to make computer challenge for saliency computation.

4.3.2 Performance Measures

To evaluate the performance of the proposed method with other state-of-art methods, we used four performance matrix (1) Precision-Recall Curve (PR-Curve),(2) Receiver Operating Characteristic (ROC-curve), (3) Mean Absolute Error (MAE)and(4) F-Measure.

4.3.3 Parameters and Constraints Selection

A set of extensive experiments is performed to evaluate the final value of the various parameters and constraints. These experiments are performed on RGB-1000 and PU-80, RGBD dataset. To make the algorithm efficient and better performance in complex and clutter images scenario. These extensive experiments have been finalized value and range of the following parameters. The outer border of the salient object is enclosed with reference contour by combined the result of applying several DoG base edges. The range of σ_1 and σ_2 varies to keep the value of $\varphi = \sigma_1/\sigma_2$ is constant as 1.6. The controlling parameter σ^2 is 0.4 in Eq.4.4.

4.3.4 Successive steps validation

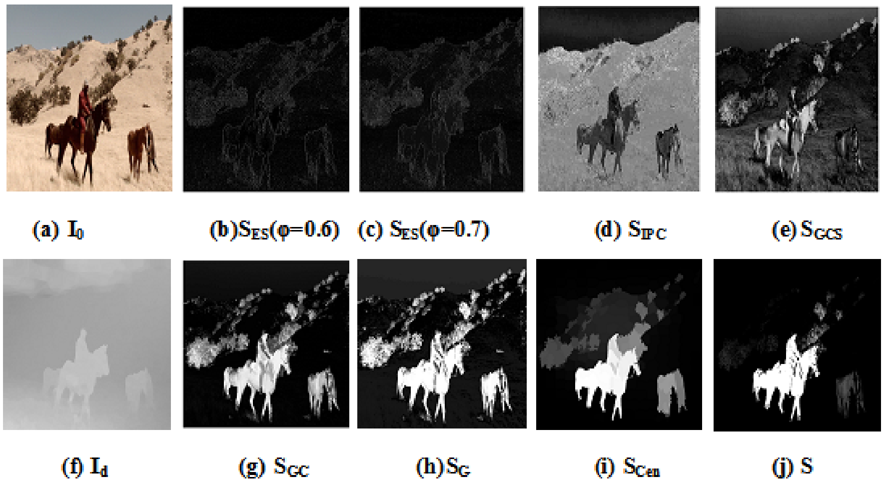

FIGURE 4.3: Visual demonstration of Contribution of each step in GCS

Successive step of proposed method GCS is validated on the Complex Image Dataset PU-80 and RGBD-1000 publicly available dataset having depth information. Validation of each step is very necessary to demonstrate the contributions in saliency. In complex and clutter background images, salient object cannot be separable by single stage algorithm. visual contribution of each step is shown in Fig.4.3. The validation of effectiveness is measured through MAE(mean absolute error) and Table4.1. The result is shown in Table4.1. which, validates each step of GCS on PU-80 and RGBD-1000 datasets. This result demonstrates the effectiveness of each step.

TABLE 4.1: Steps wise Mean Absolute Error-MAE in proposed Method-GTS

$Data - Set$	$Initail\ S_{GCS}$	$Final\ S_G$	S_{Cen}	S
PU-80	0.5875	0.3605	0.1593	0.0716
RGBD-1000	0.3540	0.2451	0.1097	0.0581

4.3.5 Comparative Analysis

The extensive experiment of the proposed method, GCS (Global Concave Saliency) is performed on using two RGBD benchmark datasets having images with complex and clutter background. This result analysis of the proposed method is evaluated through a visual qualitative Fig.4.4 and quantitative scale. Our proposed method initialized with global probabilistic contrast and difference of Gaussian based contour model. Therefore in these evaluations, The top five global contrast-based methods like MDC [5], HC [4], GC [62], MSS [66], FT [11] are selected.

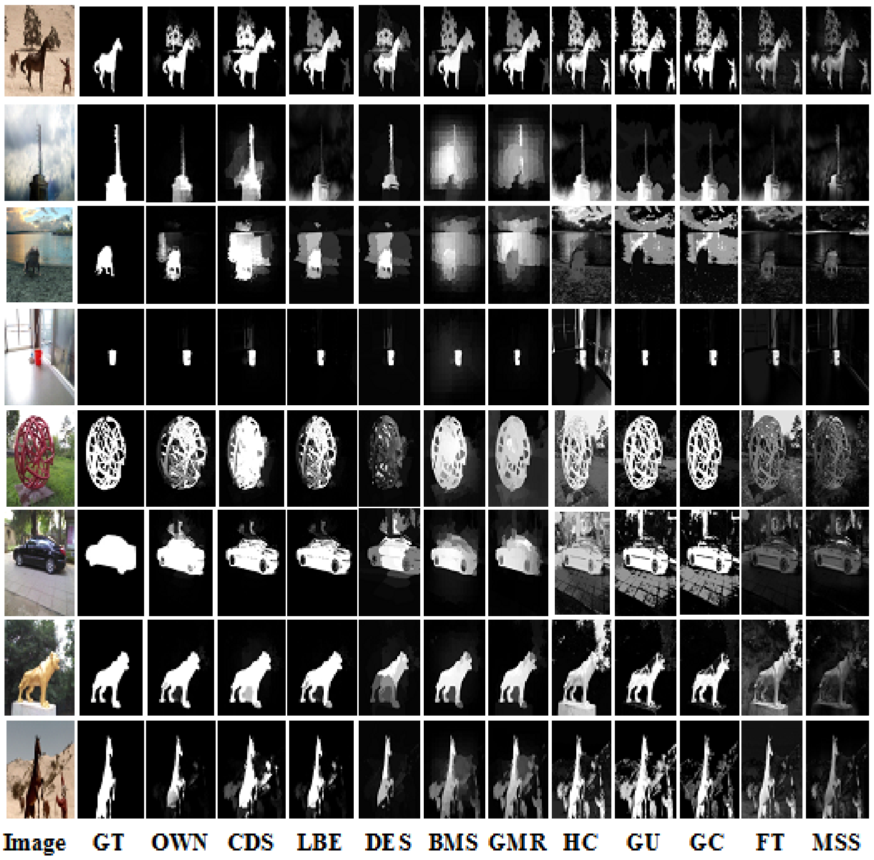

FIGURE 4.4: Visual comparison of saliency of proposed method with other state-of-art methods.

These methods are selected in these result analysis are based on highly referenced, computationally fast, recent, and closely related to our proposed method. The Proposed method GCS is also compared with efficient graphical model GMR and cellular automata-based central saliency model BMS. The proposed method is also compared with top, efficient, and recent RGBD based models like LBE, CDS, and DES. This evaluation , some other state-of-art methods like GU [68], RC [4], RBD [12], MST [42], are compared using Mean Absolute Error MAE in Table 4.2.

The Qualitative analysis is demonstrated through the visual saliency-map, which is shown in Fig.4.4. In this observation, the global contrast-based methods produce full-length saliency. The global contrast-based process, FT, GC, MDC, HC, and MSS are highlighting some background similar to the salient regions and suppressing some interior saliency, which has similar characteristics with the background. So these methods produce interior and exterior saliency discrepancy both. To remove the backgrounds HC, RC used Saliency-Cut, FT used Mean-shift, MSS used Graph-cut algorithm, which further enhanced the computation cost. MDC used a Marker-based watershed segmentation algorithm to separate the salient object. This method destroys some structural information like shape, border regions, which is shown in Fig.4.4.

The Marker-based watershed segmentation algorithm produces multiple markers, in which some are related to background and others to the objects. Cellular automata-based central saliency creates a saliency map with no interior saliency discrepancy

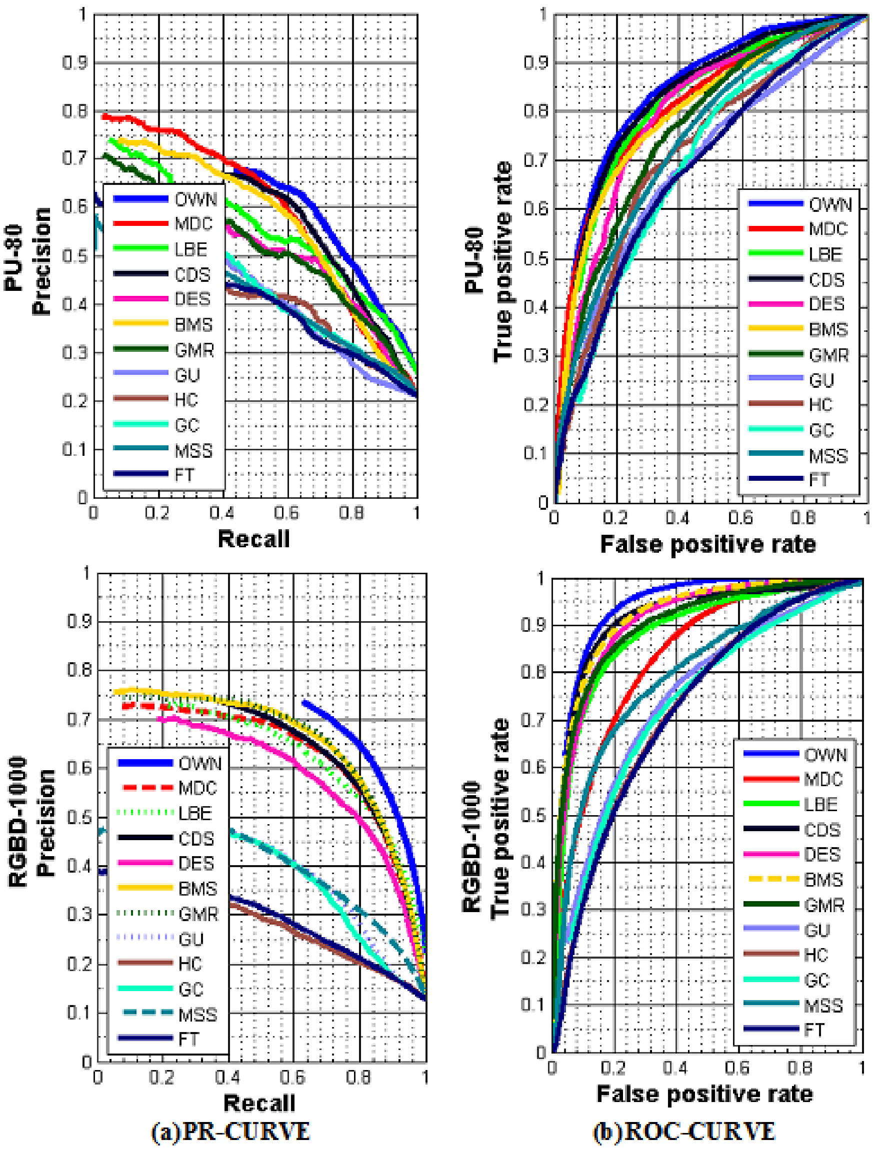

FIGURE 4.5: Quantitative comparison of proposed method GCS with PR-Curve and ROC-Curve.

but failed on object boundary. Therefore, this algorithm used in saliency enhancement. All the above methods are failed in producing saliency in low depth images. The proposed method, GCS, minimized the above-mentioned limitations and built a robust salient object, which is reduced the interior saliency discrepancy and altogether remove the backgrounds in low depth and sophisticated image. Through

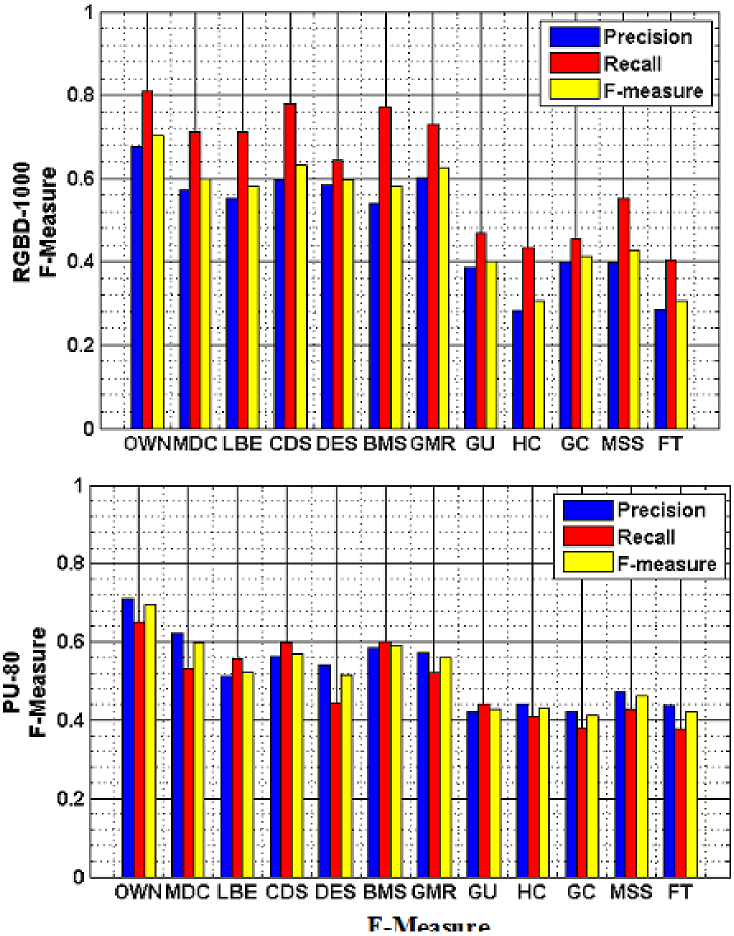

FIGURE 4.6: Quantitative comparison of proposed method with F-Measure

visual comparisons, the proposed method can detect single, multiple, and complex images precisely. Through all these observations, our proposed method GCS performs better than other state-of-art methods.

TABLE 4.2: Mean Absolute Error-MAE of different state-of-the-art methods

	FT	HC	GMR	MDC	BSA	LBE	DES	CDS	OWN
PU-80	0.2324	0.2310	0.2298	0.1957	0.1889	0.3158	0.1156	0.0958	0.0716
RGBD-1000	0.2049	0.2169	0.2249	0.1969	0.1806	0.1783	0.2931	0.0731	0.0581

The proposed method GCS is compared with ten state-of-the-art top-performing methods using PR-Curve, ROC-Curve and F-Measure Fig.4.5 and Fig.4.6. While the top twelve methods are compared using MAE. The proposed method outperforms on the recall axis while maintaining the same level of precision, which is visible in PR-Curve. These characteristics demonstrate the robustness of the proposed method GCS with better saliency maps with other state-of-art methods.

4.3.6 Comparison with other Own proposed methods

The proposed method CGS is also compared with other two probabilistic based models *PC PC+*. The comparison is shown in Fig. 4.7 which clealy demonstrate that improved probabilistic contrast with global concave topographical surface-GCS perform batter in 3D RGBD data-sets.

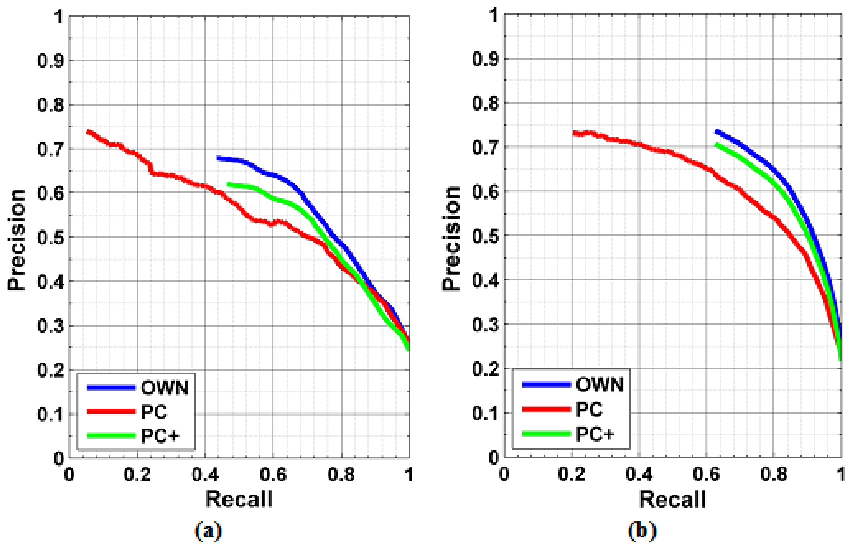

FIGURE 4.7: Comparison of GCS with other proposed own probabilistic contrast based method using PR-Curve

4.4 Conclusion

This method used an additional parameter depth to increase the robustness in saliency detection in complex and clutter background. In this method, an innovative and robust approach of global concave topographical surface (GCS) is prepared for regional features integration. This surface designs with the difference of Gaussian based contours. So, this reference plane is used to minimize the border region's discrepancies. This integration works efficiently and effectively in regional saliencies integration to reduce the interior, exterior, and regional saliency discrepancies. The robustness of GCS increases the preservation of the structure, shape, and border-related information in saliency estimation. These regional saliencies integrations remove the interior saliencies discrepancies. Gaussian weighted background estimation and central saliency integration remove the exterior saliencies discrepancies. Finally, all these integrations into the global concave surface plane are increasing robustness and achieving state-of-the-art results. The improvements in robustness are the direction of the future works on this framework.

Further research will be focused on improving outcomes for these complex datasets. Deep learning algorithms have not been considered in this chapter. Results from deep learning are very appealing, and efforts can be put in generating deep learning based model to further improved the salient object detection.