# Application of Conditional Random Fields in Pixel-Level Salient Object Detection within Image using Local, Regional, and Global Features

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# Introduction and Motivation

Fig.1 Images from MSRA dataset B

Saliency is the prominence of an object in an image.

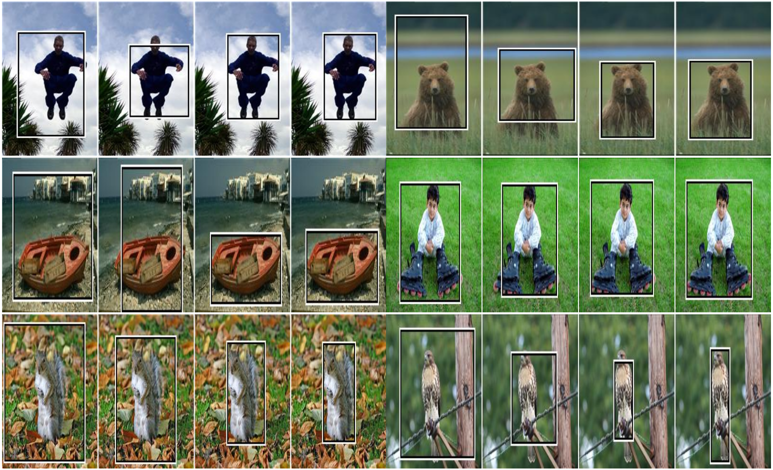
Often detected by its high contrast to its boundary with the background, its unique colour distribution compared to its surrounds, and the break in spatial continuity of colour that it represents in the image.

Salient object detection is useful in numerous areas!

# Related Works

- Salient-based Model (SM,1998)
  - Itti, Laurent, Christof Koch, and Ernst Niebur. "A model of saliency-based visual attention for rapid scene analysis." *Pattern Analysis and Machine Intelligence, IEEE Transactions on 20.11 (1998): 1254-1259.*
- Fuzzy Growing Method (FG,2003)
  - Ma, Yu-Fei, and Hong-Jiang Zhang. "Contrast-based image attention analysis by using fuzzy growing." *Proceedings of the eleventh ACM international conference on Multimedia. ACM, 2003.*
- CRF-based Model (CRFM,2007)
  - Liu, Tie, et al. "Learning to detect a salient object." *Computer Vision and Pattern Recognition, 2007. CVPR'07. IEEE Conference on. IEEE, 2007.*
  - iu, Tie, et al. "Learning to detect a salient object." *Pattern Analysis and Machine Intelligence, IEEE Transactions on 33.2 (2011): 353-367.*

# Comparisons between Existing Approaches



(a) FG(Ma,2003) (b) SM(Itti,1998) (c) CRFM(Liu,2007) (d) Ground truth

# Formulation

Given an image $I$, we want to compute the location of a salient object.

Binary labelling task – for each pixel $x$, indicate whether it belongs to the salient object (1) or not (0). Thus, our objective is to have corresponding map $A$, indicating binary saliency of one pixel.

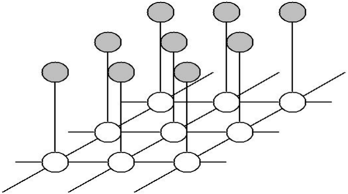


Fig.2 Conditional Random Field

Build up a probabilistic model $P(A|I) = \frac{1}{Z}e^{-E(A|I)}$, where $\frac{1}{Z}$ is the normalising factor, and $E(A|I)$ is the energy function incorporating both unary and pairwise potentials between pixels.

## Pairwise Feature

Formally, the energy function can be represented as

$$E(A|I) = \sum_{x} S_{unary}(a_x, I) + \lambda_0 \sum_{x,x'} S_{pair}(a_x, a_{x'}, I)$$

where $\lambda$ is the relative weight between the summary of multiple unary features and pairwise features.

The pairwise feature $S(a_x, a_{x'}, I)$ exploits the spatial relationship between two adjacent pixels. It can be viewed as a "penalty" for labelling adjacent pixels the same or differently.

$$S(a_x, a_{x'}, I) = |a_x - a_{x'}| \cdot e^{-\beta d_{x,x'}}$$

where $x, x'$ represent two adjacent pixels, $d_{x,x'}$ is the L2-norm (standard norm) representing the colour difference between the two pixels, and $\beta = (2\langle||I_x - I_{x'}||^2\rangle)^{-1}$ is a robust parameter to weight the colour contrast.

## Unary Features Combination

The unary potential for combination of three features is specified as

$$S_{unary}(a_x, I) = \sum_{k=1}^{K} \lambda_k \cdot F_k(a_x, I)$$

where $\lambda_k$ is the weight of the $k^{th}$ feature conforming to $\sum_k^K \lambda_k = 1$.

Fig.3 Preview of feature maps

The value of each feature $F_k(a_x, I)$ comes from a normalised feature map $f_k(x, I) \in [0, 1]$, and for each pixel:

$$F_k(a_x, I) = \begin{cases} f_k(x, I), & a_x = 0 \\ 1 - f_k(x, I), & a_x = 1 \end{cases}$$

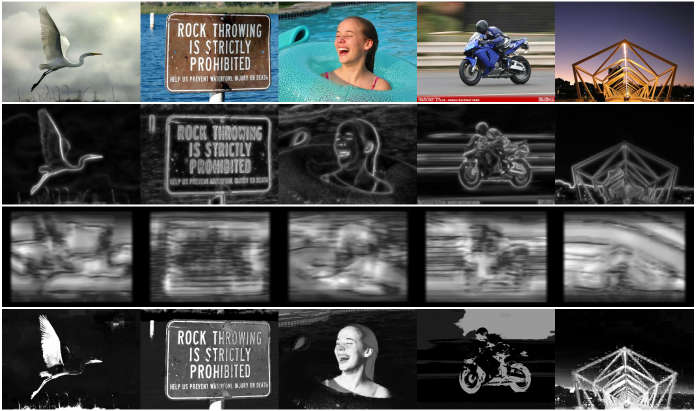
# Learning

The values from the before-mentioned features are accumulated in a CRF model, which the dataset then trains on. MORE DETAIL HERE

# Inference

CRF INFERENCE HERE

# Feature Extraction




From Top to Bottom Row: (1) Original Image (2) Local: MultiScale Contrast (3) Regional: Center-Surround Histogram (4) Global: Color Spatial Distribution

## Local: Multiscale Contrast

Create a contrast map from the linear combination of image contrast at all levels of an N-level gaussian image pyramid, using the pixels $x$ in the image $I$:

$$f_c(x, I) = \sum_{n=1}^{N} \sum_{x' \in W(x)} ||I^n(x) - I^n(x')||^2$$

where W(x) is a window that delineates which area to consider for neighbouring pixels to compare contrast values.

## Regional: Center-Surround Histogram

Given a rectangle $R_s(x)$around a salient region, create a frame $R(x)$ around it so that the area of the frame is equal to that of the rectangle (this is displaced as needed to fit into the image dimensions), at a suitable aspect ratio.

PICTURES HERE.

## Regional: Center-Surround Histogram

Create a colour RGB histogram for both the rectangle and the surrounding frame with a certain resolution (number of "bins" for each colour)

Calculate the $\chi^2$ value between the two histograms to obtain the differences between the rectangle and the surrounding frame. Do this for multiple aspect ratios, and keep the largest $\chi^2$ value:

$$R(x) = \arg\max_{R(x)} \chi^2(R(x), R_s(x)) = \arg\max_{R(x)} \frac{1}{2} \cdot \sum_{i \in bins} \frac{(hist_{R(x)_i} - hist_{R_s(x)_i})^2}{hist_{R(x)_i} + hist_{R_s(x)_i}}$$

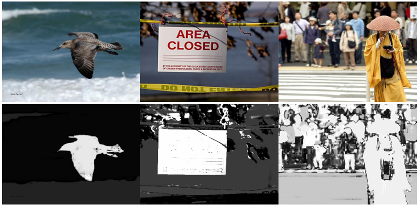
The center-surround histogram feature is finally calculated as:

$$f_h(x, I) \propto \sum_{x' | x \in R(x')} w_{xx'} \chi^2(R(x'), R_s(x'))$$

## Global: Colour Spatial Distribution

Create a Gaussian Mixture Model to compute the spatial variance and continuity of colour in an image.

The component model is created from only a subset of the pixels in the image, and the maximum number of iterations is limited in order to reduce the time taken to compute this feature without sacrificing too much accuracy.



## Global: Colour Spatial Distribution

Each pixel is associated to a colour component with the probability

$$P(c|I_x) = \frac{\omega_c \mathcal{N}(I_x|\mu_c, \sigma_c)}{\sum_c \omega_c \mathcal{N}(I_x|\mu_c, \Sigma_c)}$$

where $\omega_c$ is the weight, $\mu_c$ is the mean colour, $\sigma_c$ is the covariance, and $\mathcal{N}(I_x|\mu_c, \sigma_c)$ is the multivariate normal distribution of the $c^{th} component$

The final colour spatial distribution feature is defined as a weighted sum:

$$f_s(x, I) \propto \sum_c p(c|I_x) \cdot (1 - V(c))$$

where $V(c)$ is the normalised covariance (horizontal and vertical variances) of the $c^{th}$ component, contained between 0 and 1.

# Thank you! Questions?

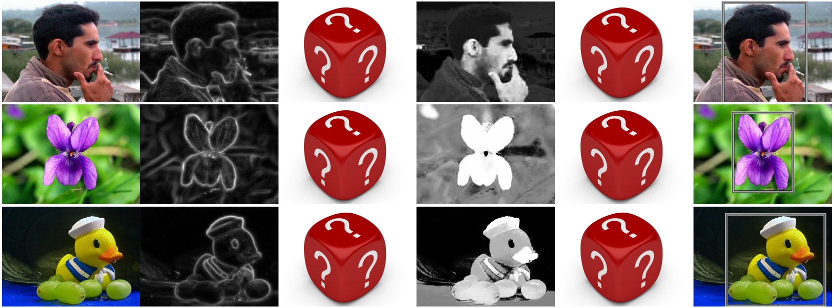


Fig.5 Our implementation

## References


- Liu, Tie, et al. "Learning to detect a salient object." *Computer Vision and Pattern Recognition, 2007. CVPR'07. IEEE Conference on. IEEE, 2007.*
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- Ma, Yu-Fei, and Hong-Jiang Zhang. "Contrast-based image attention analysis by using fuzzy growing." *Proceedings of the eleventh ACM international conference on Multimedia. ACM, 2003.*
- Stephen Gould, "DARWIN: A Framework for Machine Learning and Computer Vision Research and Development", *Journal of Machine Learning Research (JMLR), 13(Dec):35333537, 2012.*