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.

Salient object detection is useful in numerous areas! For instance, Simulate the human vision by robots. Augmented Reality. Automatic image compression.

Often detected by its **boundary of high contrast** to its near neighbours, **distinct to its surrounded block**, **intensive colour distribution** compared to all other color component in candidate image and **space continuity of saliency**.

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.*
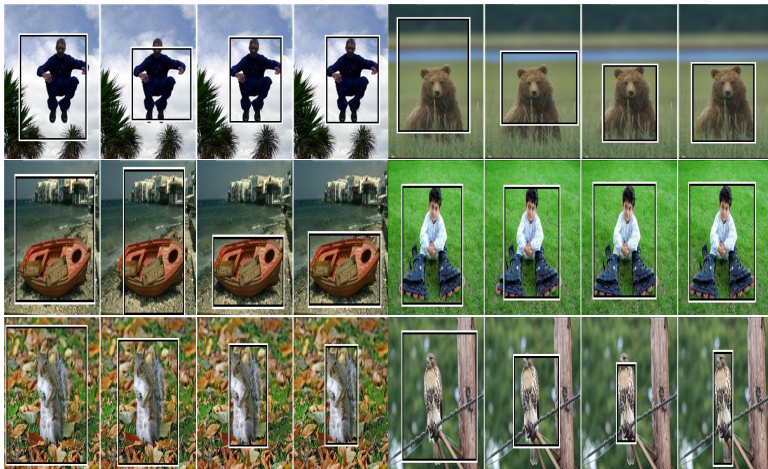
- CRF-based Model (CRFM,2007)

  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.
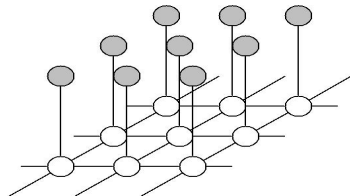

Fig.2 Conditional Random Field

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 λ 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 λ_k is the weight of the kth 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:

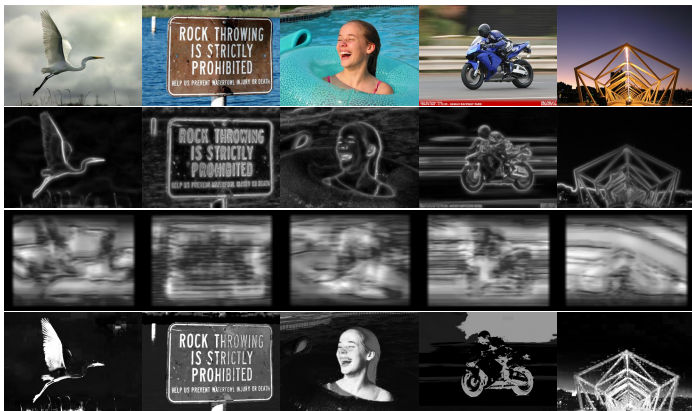$$F_k(a_x, I) = \begin{cases} f_k(x, I), & a_x = 0 \\ 1 - f_k(x, I), & a_x = 1 \end{cases}$$

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.
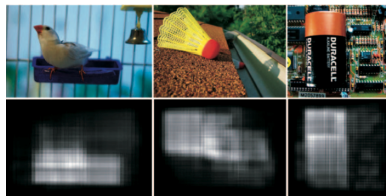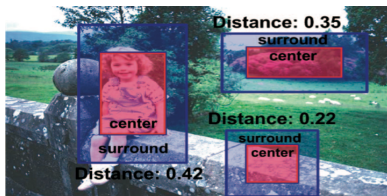
Liu, Tie, et al. "Learning to detect a salient object." *Computer Vision and Pattern Recognition, 2007. CVPR'07. IEEE Conference on. IEEE, 2007.*

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 χ^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 χ^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.
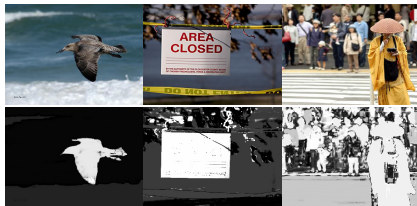
Global: Colour Spatial Distribution

Each pixel is associated to a colour component with the probability

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

where ω_c is the weight, μ_c is the mean colour, σ_c is the covariance, and $\mathcal{N}(I_x|\mu_c, \sigma_c)$ is the multivariate normal distribution of the cth 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 cth component, contained between 0 and 1.
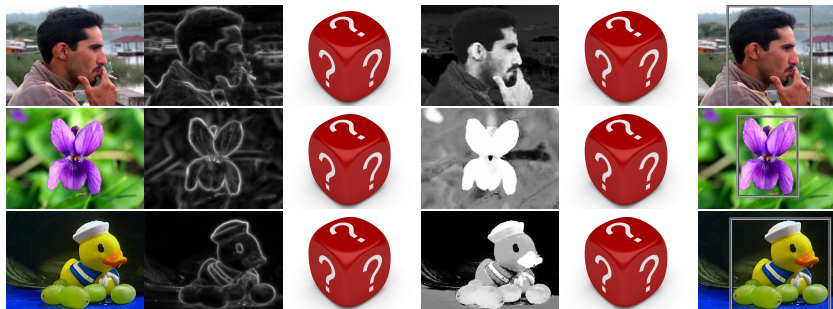
Our Project Progress

Fig.5 Our implementation
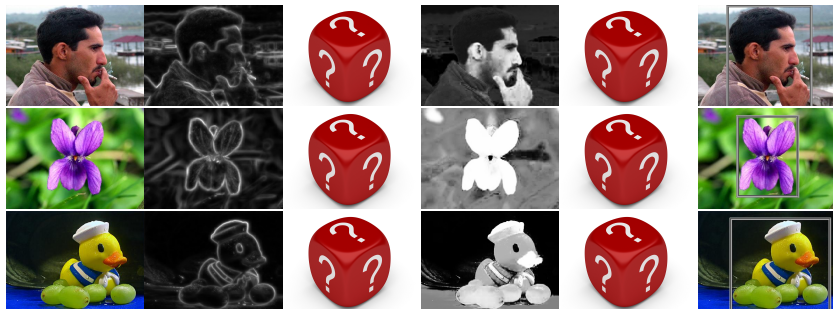
Thank you! Questions?

Fig.5 Our implementation

References

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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.*