Application of Conditional Random Fields to Pixel-Level Salient Object Detection Through Local, Regional and Global Features

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Abstract

Making use of OpenCV, DARWIN and the MSRA dataset, we detect the saliency of an object in an image by extracting local, regional and global features at the pixel level, combined with pre-fitted weights derived via logistic regression. A conditional random field is then constructed to capture the spatial continuity of the salient object, with a weighting ratio of combined unary and pairwise terms determined through cross-validation. The binary mask inferred by the conditional random field is then used to output a single bounding rectangle around a salient area through a winner-takes-all algorithm to label the detected salient object, by which the performance of our approach is evaluated through precision, recall and F-measure values as well as mean boundary displacement error. The results show that the algorithm is overall highly precise but at the cost of its recall, due to flaws in the bounding box output algorithm and the major dependence on colour for saliency detection.

1. Introduction and Motivation

A long-standing problem in the field of computer vision is how to calculate the saliency of objects in an image, that is, their prominence in the image when compared to their background and surrounds. Human vision can accomplish this quite easily, since the human brain has mechanisms to direct attention to the main objects in the perceived image. This ability has been studied by researchers in multiple fields, from physiology and psychology, to computer science. The property of detecting a salient object is important for the latter because it leads to the ability to single out individual areas of an image, for example in automatic image cropping and vision simulation in robotics, as well as 3D surface reconstruction in augmented reality displays. Salient object detection is still a field of active research, with multiple avenues being currently pursued.

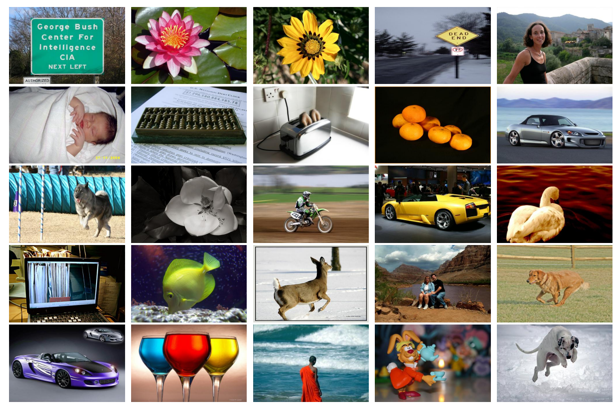


Figure 1. Example images from MSRA dataset B

2. Related Works

Most existing approaches are based on a bottom-up computational framework, where the computer's simulation of visual attention is driven by low-level stimuli in the scene [4][5][8]. These approaches employ three steps, the first of which is feature extraction. Multiple low-level visual features such as intensity, colour, orientation, texture, and motion are extracted from the image at multiple scales and are then incorporated into a framework to aid in the detection of the salient object.

The second step is saliency computation. The saliency is computed by a centre-surround operation, self-information, or graph-based random walk using multiple features. After normalisation and linear/nonlinear combination, a master or saliency map is computed to represent the saliency of each pixel in the image.

Finally, a few key locations on the saliency map are identified by winner-take-all, inhibition-of-return, or other nonlinear operations and are returned as a label designating the salient area in the image.

3. Our Approach

In our approach, we use the open source DARWIN machine learning framework [3] as the basis for our code. We employ the MSRA dataset as the base images for our salient object detection, and build an algorithm from several assumptions that relate to how human vision differentiates salient objects from the rest of the perceived field of view. People naturally pay more attention to salient objects in images, such as a person, a face, a car, an animal, or a road sign (Figure 1). This attention can be mimicked in computer vision through several factors, which were brought forward by Liu et. al in their research [6][7].

It is likely that pixels with a high contrast difference to their near neighbours are part of a salient object, since they could represent a contour or boundary around such an area. This is similar to how the human brain determines boundaries between objects in its visual field through differences in light intensity.

Salient objects are more often than not quite distinct from their local surrounding region. Calculating the difference between an object and its surrounds can therefore give us information about how salient that object is. If we apply this concept over the entire image, we can gather information about how different various areas are to their surrounds to work out the likelihood that those areas are salient.

Finally, humans perceive object prominence through how distinctly coloured they are compared to the rest of the visual field. Indeed, salient objects often demonstrate a marked difference in colour to the rest of a scene. Therefore, the more widely distributed a colour is in an image, the less likely it is that the salient object will contain that colour. The global colour distribution in an image can therefore be used to describe the saliency of the pixels contained within.

3.1. Formulation

To turn the problem of salient object detection into a mathematical formulation, we incorporate these three high-level concepts into the process of creating a saliency map. Salient object detection can be thus formulated as a binary labelling task that separates a salient object from the background through multiple operations.

For each pixel x of a given image I, the binary mask A_x must indicate whether it belongs to the salient object (1) or not (0). Our objective is to compute this mask A in order to show the location of the salient object in the image.

To do this, we build up a probabilistic model

$$P(A|I) = \frac{1}{Z} \cdot \exp(-E(A|I))$$

to determine the probability of a binary mask over an image with $\frac{1}{Z}$ as the normalising factor, and $E(A|I)$ as an energy function incorporating both unary and pairwise potentials between pixels in the image

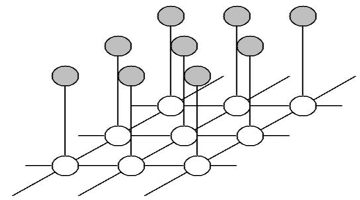


Figure 2. A Conditional Random Field
White nodes are binary saliency potentials, grey nodes are composite pixelwise features

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_0 is the relative weight between the sum of multiple unary and pairwise features.

The unary potential, combining the three pixel 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 k^{th} feature.

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 differently:

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

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.

The final energy map $F_k(a_x, I)$ is calculated from the normalised feature map $f_k(x, I) \in [0, 1]$, where for each pixel:

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

Each pixel is given a penalty if its feature map value $f_k(x, I)$ shows it is not predicted to be within the salient object ($a_x = 0$).

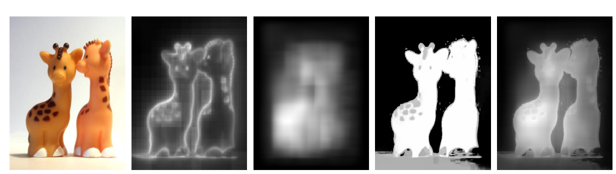


Figure 3. Original Image and Preview of feature maps
Left to Right: Original Image, Multiscale Contrast Map, Centre-Surround Histogram, Colour Spatial Distribution, Composed Unary Potentials

3.2. Feature Extraction

Feature Extraction, widely acknowledged as the most significant component of a computer vision task, represents how we want the computer to interpret raw images. In this project, we focus on three features capable of capturing saliency individually but in different levels of scope. They are respectively multiscale contrast, centre-surround histograms and colour-spatial distribution.

Because of the time expense required to calculate these features on an image, our approach caches the feature maps of each image and uses them for both training and testing.

3.2.1 Multiscale Contrast

Contrast is commonly used as local feature because it simulates the human visual receptive fields. It acts on the fact that the boundary of salient objects tend to have a marked contrast to the surrounding region. Since we may have no prior knowledge about the size of salient object, we compute the contrast at multiple scales to then incorporate back into one map, since this will demarcate the various boundaries in the image. This multiscale contrast map is thus a linear combination of image contrast at all levels of an N-level gaussian image pyramid, using the pixels x in the image I. Formally, this amounts to calculating

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

where W(x) is a window that delineates which area to consider as neighbouring pixels to compare contrast values. The resulting map highlights the edges of different objects in the image, giving high prominence to the contours around the salient object.

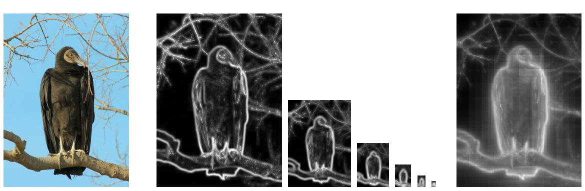


Figure 4. Multiscale Contrast.
Left: Original Image. Right: Multiscale Contrast Map.
Middle: Multiscale contrast pyramid from levels 1 to 6.

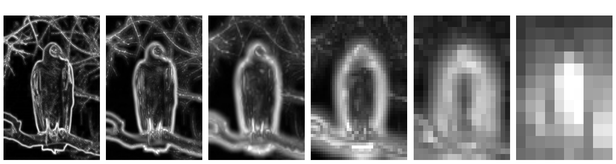


Figure 5. Multiscale contrast pyramid from levels 1 to 6.

(a) (b) (c) (d)

Figure 6. Multiscale Contrast Feature Maps

In our implementation, we choose the total number of pyramid level N to be 6 and the size of the window W to be 9×9.

As can be seen in Figure 4, the derived multiscale contrast map provides a highly accurate distinction between boundary and non-boundary pixels. This provides us a precise description of where the boundary of a salient object should exist in the output binary mask. When a salient object also has high contrast inside its boundaries, this feature also manages to capture the inside of the salient object, such as the house and bird in Figure 6.

However, there are some drawbacks that are hard to avoid. Salient objects are not just detected by their boundaries, since doing so would give a high probability to all edges regardless of whether they belong to the salient object or not. This can result in a “saliency leak” into other areas of the image that could deteriorate the detector’s precision.

Another disadvantage of using only multiscale contrast is that the inner regions of salient objects are poorly represented. For example in the gorilla in Figure 6, the teeth are labelled as higher contrast to their surroundings compared to that of the body of the gorilla to the grass. Since each entry of the output feature map is quantitatively normalised, the contrast of the gorilla’s body to the grass is rendered trivial compared to the contrast of the tooth. This is not what the human receptive field would label as salient because it is a smaller part of the whole object, and thus it should not be labelled as the entire object when detected. This flaw may result in low recall when compared to the ground truth data if contrast is used as the sole method to distinguish a salient object.

3.2.2 Centre-Surround Histogram

Multiscale contrast only partially detects salient objects, since it is only sensitive to the boundaries. In order to detect the object as a whole, we make use of another static salient feature which captures the regional information of an area, computed using various low-level features in a centre-surround distance calculation.

To do this, we create a colour RGB histogram for both the rectangle and a surrounding frame with the same area, at a certain resolution (number of "bins" in the histogram). We then measure the difference between the area centred at each pixel x and its surrounds by calculating the chi-squared distance between the two histograms representative of those regions. We do this for multiple aspect ratios $\{0.5, 0.75, 1.0, 1.25, 1.5\}$, and keep the largest (most distinct) chi-squared value through the formula

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

To reduce the computational complexity involved in this calculation, the size of the rectangle bounding the area in the centre is reduced to 12 discrete ratios {0.18, 0.2, 0.25, 0.3, 0.35, 0.4, 0.45, 0.5, 0.55, 0.6, 0.65, 0.7, 0.75} with regards to $min(w, h)$, the minimal value of width and height of the processed image.

The centre-surround histogram feature map at each pixel x is calculated by

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

where $w_{xx'}$ is a falloff weight to reflect how distinct each pixel is from its surrounds, assigned from the largest χ^2 value for the area centred at each pixel of the image and its surrounds, and its distance from the centre of that area.

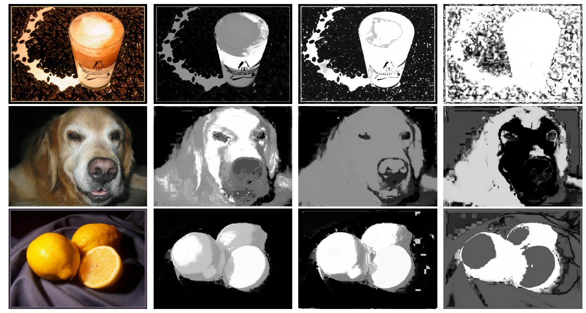
As shown in Figure 7, the salient block within the image is given significant emphasis in the output feature map when compared to its surrounds. However, unlike multi-scale contrast, the centre-surround histogram does not provide an accurate description of the boundary of the object Used together with the multiscale contrast map, the two features complement the weaknesses to create a stronger sense of the location of salient objects.

3.2.3 Colour Spatial Distribution

The goal of using colour spatial distribution is to take into account the global colour information in the image, that is,

(a) (b) (c) (d)

Figure 7. Centre-Surround Histogram Feature Maps



(a) (b) (c) (d)

(a) Original (b) No reduction (c) Single Level Reduction
(d) Two Level Reduction

Figure 8. Example Colour Spatial Distributions on Reduced Pixels

the information about how widely the colours that occur in one image are distributed within it. The computation of this feature is done in several parts.

First of all, we create a Gaussian mixture model with 5 components in order to capture relative colour distribution in the image. This can be represented as $\{c, \mu_c, \Sigma_c\}$ with regards to the colour component c and fit of these components, the mean colour and the covariance of the component c. We use only a subset of pixels from the whole image to save on computational time required to process the feature, while at the same time not losing much accuracy as can be seen in Figure 8.

We tested three levels of pixel reduction via a Gaussian image pyramid: none, single-level reduction, and two-level reduction. Single-level reduction halves the number of pixels used in creating the gaussian mixture model, whilst also providing a smoother distribution without sacrificing required accuracy.

The maximum number of iterations over the image is limited to 100 instances, and the convergence criterion is also lowered to 10^{-1} in order to reduce complexity without deteriorating the model. Such simplification is possible only because the exact distribution is not required for capturing the approximate location of a salient object.

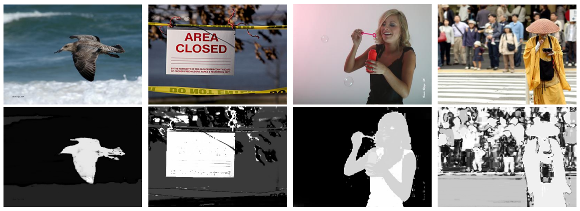
Using this model, each pixel is associated to a colour component with the probability

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

where 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 c^{th} component.

For each fitted colour component c, we compute its horizontal variance $V_h(c)$ by

$$V_h(c) = \frac{1}{|X|_c} \sum_x p(c|I_x) \cdot |x_h - M_h(c)|^2$$



(a) (b) (c) (d)

Figure 9. Colour Spatial Distribution Feature Maps

where x_h is horizontal coordinate of pixel x, $|X|_c$ is the normalising factor and $M_h(c)$is the mean of the gaussian component such that

$$|X|_c = \sum_x p(c|I_x) M_h(c) = \frac{1}{|X|_c} \sum_x p(c|I_x) \cdot x_h$$

Its vertical variance $V_v(c)$ is defined similarly, and we combine the horizontal and vertical variances to derive the unnormalised composite variance $V'(c)$:

$$V'(c) = V_h(c) + V_v(c)$$

We then employ a min-max approach to normalise the composite covariance over the image

$$V(c) = \frac{V'(c) - min\big(V'(c)\big)}{max\big(V'(c)\big) - min\big(V'(c)\big)}$$

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

Finally, due to the assumption that a salient object tends to have a less widely distributed colour, we set a penalty for the pixels which are described by a highly-distributed colour. The colour spatial distribution map is therefore defined as a weighted sum of its colour distribution of each pixel.

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

The final feature map $f_s(x, I)$ is normalised to fall between $[0, 1]$. Figure 9 demonstrates the colour spatial distribution feature map on several images. The salient objects are labelled effectively by this global feature when there is a high distribution of other colours in the image.

It is evident that this global feature allows the detector to find salient objects with much greater accuracy when the background is monotonous. However, in the case of a varied and colourful background, the colour spatial distribution map fails to distinguish the salient object in the image. Figure 9 (d) demonstrates us this undesired property of colour spatial distribution, because the background is full of multiple single coloured areas that do not occur anywhere else in the image.

3.3. Learning

The three features discussed beforehand all have strengths and weaknesses in different areas, adding them together provides an accurate description of the salient area in an image. It would be over-simplistic to weight these features equally, since one feature may be better than the others at providing information about image saliency. One effective and reasonable approach to determine the optimal weights to combine the three features with is through the help of a machine learning algorithm. In this report, we use logistic regression to decide the optimal weight on training data.

As mentioned before, the salient object detection is formulated as a binary decision problem. From this perspective, we can directly compute the posterior distribution over the binary saliency variable A_x as a sigmoid function

$$y_x = p(A_x = 1|\boldsymbol{\phi}_x) = \frac{1}{1 + \exp(-\boldsymbol{\lambda} \cdot \boldsymbol{\phi}_x)}$$

where the vector $\boldsymbol{\phi}_x$ contains three normalised energy parameters $F_k(x, I)$ for each pixel x, and the vector $\boldsymbol{\lambda} = \{\lambda_1, \lambda_2, \lambda_3\}$ indicates how the three extracted features form the unary term in the energy function are used in the inference model.

The likelihood function of an image with given human label $\boldsymbol{t}$ can be defined as

$$p(\boldsymbol{t}|\boldsymbol{\lambda}) = \prod_x y_x^{t_x} (1 - y_x)^{1-t_x}$$

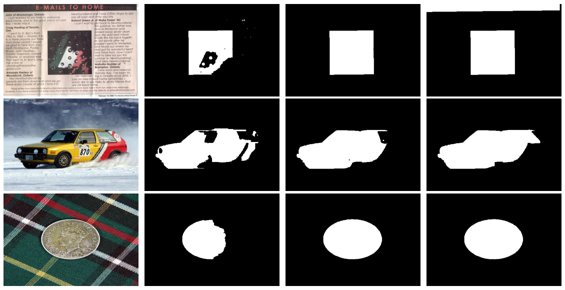
where the target variable $\boldsymbol{t}$ is the ground truth map, and $\boldsymbol{t}_x$ indicates the human label of the saliency of the pixel x.

We apply a maximum likelihood estimation to evaluate the parameter $\boldsymbol{\lambda}$, based on the above likelihood function. Under this logistic regression framework, the optimal value of $\boldsymbol{\lambda}$ is $\{1.58137, 2.62738, 0.563939\}$.

3.4. CRF Inference

The combined unary potential made up from these weighted feature maps is likely to already provide a good estimate of the salient area in the image. However, to capture the spatial continuity of the salient area we infer the maximum likelihood assignment of pixelwise variables under a conditional random field (CRF) framework. A standard message-passing approach is infeasible when dealing with images at the pixel level, so we instead use α-expansion inference, which successively segments all α and non-α pixels using graph cuts [1]. The algorithm changes the value of α at each iteration using the graph cut algorithm; by this means, inferring the maximum likelihood assignment for each binary variable (or equivalently, the minimal energy function) is much faster.

This requires a way to determine the parameter λ_0 which indicates to what extent, relative to the unary potential of



(a) (b) (c) (d)

(a) Raw Image (b) $\lambda_0 = 1$ (c) $\lambda_0 = 10$ (d) $\lambda_0 = 100$

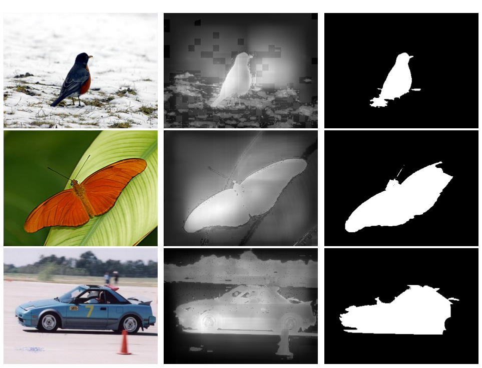
Figure 10. Examples for Binary Mask with various $\lambda_0 values$

the combined feature map, the algorithm should consider the pairwise potential in deciding the binary saliency of a pixel. This parameter is key to influencing the smoothness of the resulting binary mask, since as discussed above it can be regarded as a penalty for labelling adjacent pixels with different values.

λ_0	0.1	1	10	50
Precision	0.694	0.761	0.866	0.0
Recall	0.520	0.618	0.619	0.0
F-measure	0.589	0.659	0.704	0.0
BDE	57.09	37.78	28.56	0.0

Table 1. Cross-validation example with four values

To determine a suitable value for λ_0, we apply cross validation at various magnitudes. Using this, we observe that $\lambda_0 = 10$ has a large F-measure and small boundary displacement error. We therefore use this as the optimal parameter to infer the final binary mask.



(a) Raw Image (b) Combined Unary Map (c) Binary Mask ($\lambda = 8$)

Figure 11. Examples for CRF inference by α-expansion

4. Result Evaluation

To evaluate our approach, we randomly pick 1000 images from the MSRA dataset B to form a training set. We then choose another 500 images to form a testing set.

4.1. Bounding Box

The binary mask derived from the CRF inference can be used directly in a multitude of applications. However, in order to evaluate the accuracy of our approach, we make use of OpenCV's findContours algorithm [9] to detect the contours around the salient area derived from the pixelwise binary mask. A minimum bounding rectangle is then calculated for the largest salient area in the image, and its dimensions are written to a text file holding all resultant labels for that image directory along with the image name and size for later processing.

4.2. Evaluation Criteria

The accuracy of the approach taken is shown visually in Figure 12. However, the numerical accuracy of our approach cannot be extracted from the output image. To calculate the effectiveness of our approach, we use two approaches: region-based evaluation, and boundary displacement error.

4.2.1 Region-based measurement

Precision and Recall both take significant roles as performance indicators in information retrieval. They are used in this project to evaluate the correctness of the output bounding rectangle.

Precision represents the accuracy that pixels that are correctly detected in the saliency mask. Recall reflects the percentage of pixels that are correctly labelled overall in the probability map. Examples illustrating these differences are shown in Figure 13. The label in the leftmost image has high precision but the recall is very low, meaning that it has failed to detect all truly salient pixels. The middle image is no better, with high recall but low precision because of a saliency leak into the surrounding region.

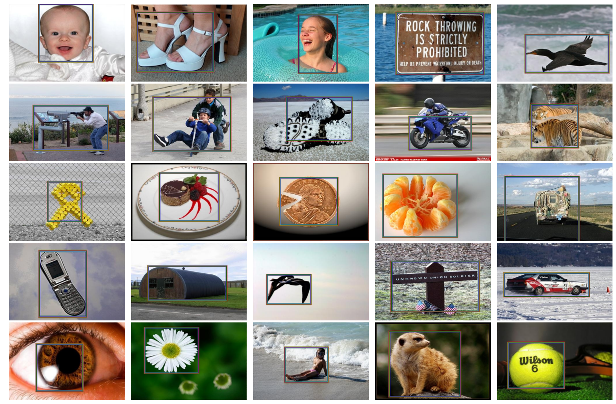
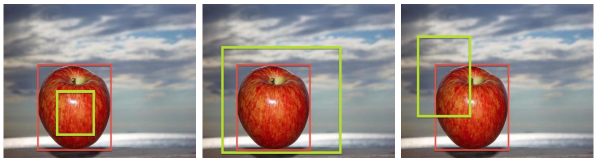


Figure 12. Example Results from our Algorithm



(a) (b) (c)

Figure 13. Examples that illustrate precision and recall
Red Box: ground truth label. Green Box: detected label.

For an overall performance measurement, the F-measure indicator with $\alpha = 0.5$ is suitable, returning the weighted harmonic mean of precision and recall:

$$F_{0.5} = \frac{1.5 \times Precision \times Recall}{0.5 \times Precision + Recall}$$

4.2.2 Boundary Displacement Error

Boundary displacement error (BDE) measures the average positional difference between the ground truth and result labels [2]. It does this by calculating the minimum Euclidian distance between the set of pixels in one label B_1 and each pixel x in the other label B_2, averaging this result over the number of pixels in the set B_1.

$$BDE(B_1, B_2) = \frac{\sum\limits_{x \in B_1} \min\limits_{y \in B_2} \{d_E(x, y)\}}{|B_1|}$$

A perfect score is 0, where every point in the result output label is contained in the set of points in the truth label. As the result labels differ more and more from the ground truth, the average BDE value becomes higher. The value itself represents the average number of pixels the result label boundaries have been displaced by as a whole, when compared to what they should be. This does not necessarily mean that the label's bounding box dimensions are proportionally the same to those of the ground truth, because smaller, larger, and offset labels can have the same boundary displacement.

4.3. Results and Discussion

The average recall and precision for our test set are 0.628987 and 0.847835 respectively. The corresponding harmonic F-measure is 0.705468 and the average BDE score is 28.4735. These scores show that the precision of our algorithm is quite high, at the cost of recall on salient objects. The BDE score demonstrates that the labels returned are off by about 28 pixels on average, which is good bot not particularly accurate.

Part of the reason for this displacement is that the contours formed around the salient area of the image are not always fully closed, leading to a highly precise bounding box rectangle around a single point of the salient area. This is due to findContours labelling it as the largest discovered closed surface. Creating a bounding box around all salient points in an image has the opposite effect in certain cases, with a large recall but multiple non-salient areas of the image contained within the bounding box because of small areas in the image where a "saliency leak" has occurred, even after CRF inference.

Another issue is that the saliency map returned from the CRF inference on images with text tend to only mark the letters in the text as salient, missing the larger area of the sign or billboard. This is a byproduct of our feature set since the letters are seen as the most distinct objects in the image. Saliency leak into the background areas is also a problem, and occurs when the salient object has a similar colour to the background of the image – this is due to the major use of colour in our feature extraction algorithms.

5. Conclusion

In this project, we have demonstrated a supervised approach for salient object detection, formulated as a binary labelling problem using a set of local, regional, and global salient object features. However, there is much room for improvement, especially in the labelling of the salient areas from the derived binary mask. There is also a lack of comparison with other methods using numerical evaluations, which may demonstrate greater effectiveness of the approach in this report.

There are still several remaining issues for further investigation. These include the ability to detect multiple salient areas in an image, improving on previous and current work to form a computational model capable of describing a scene. Another application could be in real-time detection for use in robotics and recording or playback applications.

Failure cases of the algorithm can be remedied by creating a more adept manner of finding the largest salient portion of the image, that captures the closest 98% of salient pixels. This would result in much higher numerical accuracy overall when interpreting the binary mask. There may also be better ways to derive a label from the raw binary mask of an image than finding contours or largely salient areas.

Last but not least, an inherent drawback of our pixelwise learning comes from the pseudo-correctness of the ground truth data. That is, the human-labelled rectangle may sometimes contain a large portion of pixels that are not, from the perspective of its graphical characteristics, contained in the salient object. For example, in Figure 13, the ground truth label (red box) encompasses a number of blue pixels corresponding to the sky. This noise might be emphasised at the edges of salient objects. As a consequence, the logistic regression carried out in this report may have learnt from a set of essentially erroneous pair of feature vectors $\boldsymbol{\phi}_x$ and target variable $\boldsymbol{t}_x$ and thus the resulting parameter $\boldsymbol{\lambda}$ could be suboptimal for true salient object detection.

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