REPORT

APPROACH 1:

- Here, we implemented the Research Paper:
  - Saliency Filters: Contrast Based Filtering for Salient Region Detection.(CVPR 2012)
- Entire Implementation is divided into 4 Sub-parts:
  - Abstraction:
    - For the image abstraction, we use an adaptation of SLIC superpixel to abstract the image into perceptually uniform regions.
  - Uniqueness:
    - Generally defined as the rarity of a segment given its position and color in CIELab space compared to all other segments.

$$U_i = \sum_{j=1}^{N} \|\mathbf{c}_i - \mathbf{c}_j\|^2 \cdot \underbrace{w(\mathbf{p}_i, \mathbf{p}_j)}_{w_{ij}^{(p)}} .$$

  - Distribution:
    - Conceptually, we define the element distribution measure for a segment i using the spatial variance D_i of its color c_i.

$$D_i = \sum_{j=1}^{N} \|\mathbf{p}_j - \mu_i\|^2 \underbrace{w(\mathbf{c}_i, \mathbf{c}_j)}_{w_{ij}^{(c)}},$$

  - Saliency:
    - Here, We First Normalize both Uniqueness and Distribution, then we compute Saliency S_i for each superpixel using,

$$S_i = U_i \cdot \exp(-k \cdot D_i)$$

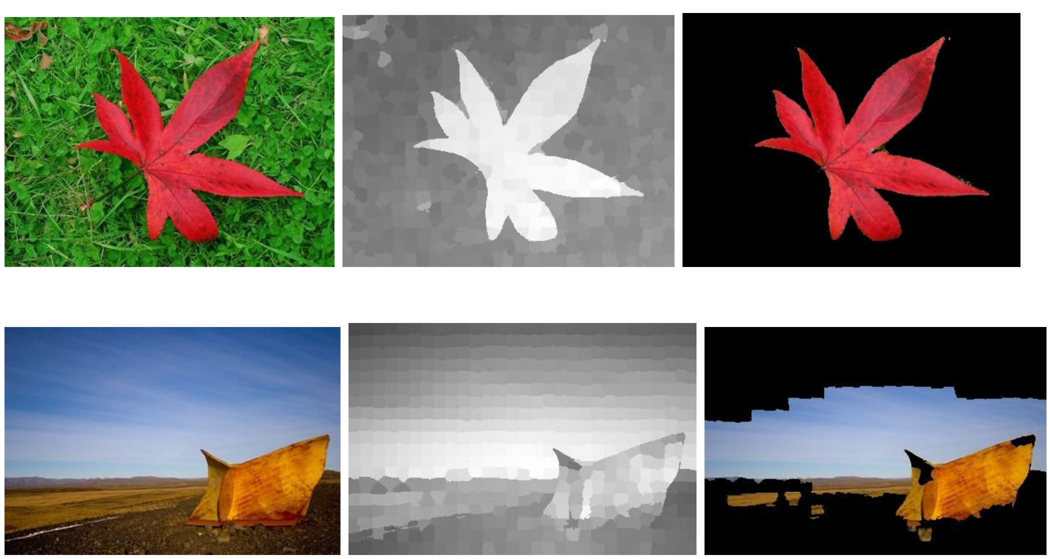
- As the final step, we need to assign a final saliency value to each image pixel, which can be interpreted as an upsampling of the per-element saliency S_i.
- We define the saliency $\tilde{S}_i$ of a pixel as a weighted linear combination of the saliency S_j of its surrounding image elements.
- By choosing a Gaussian weight as,

  $$\mathbf{w_{ij} = 1/Z_i \times \exp(-\ 1/2 \times(\alpha\|c_i - c_j\|^2 + \beta\|p_i - p_j\|^2))}$$

  we can ensure the up-sampling process is both local and color sensitive. Here, α and β are parameters controlling the sensitivity to color and position.

$$\tilde{S}_i = \sum_{j=1}^{N} w_{ij} S_j .$$

Results:



Extension to Approach-1 :

- As, In the above Approach, we noticed that some of the results are not good, So we tried to perform on pixel level instead of superpixels.

$$
\begin{aligned}
U_i &= \sum_{j=1}^{N} \|\mathbf{c}_i - \mathbf{c}_j\|^2 w_{ij}^{(p)} \\
&= \mathbf{c}_i^2 \underbrace{\sum_{j=1}^{N} w_{ij}^{(p)}}_{1} - 2\mathbf{c}_i \underbrace{\sum_{j=1}^{N} \mathbf{c}_j w_{ij}^{(p)}}_{\text{blur } c_j} + \underbrace{\sum_{j=1}^{N} \mathbf{c}_j^2 w_{ij}^{(p)}}_{\text{blur } c_j^2}
\end{aligned}
$$

$$
\begin{aligned}
D_i &= \sum_{j=1}^{N} \|\mathbf{p}_j - \mu_i\|^2 w_{ij}^{(c)} \\
&= \sum_{j=1}^{N} \mathbf{p}_j^2 w_{ij}^{(c)} - 2\mu_i \underbrace{\sum_{j=1}^{N} \mathbf{p}_j w_{ij}^{(c)}}_{\mu_i} + {\mu_i}^2 \underbrace{\sum_{j=1}^{N} w_{ij}^{(c)}}_{1} \\
&= \underbrace{\sum_{j=1}^{N} \mathbf{p}_j^2 w_{ij}^{(c)}}_{\text{blur } \mathbf{p}_j^2} - \underbrace{\mu_i}_{\text{blur } \mathbf{p}_j}{}^2.
\end{aligned}
$$

- We, used the above Formulae, and calculated the Uniqueness and Distribution using Gaussian Filters.

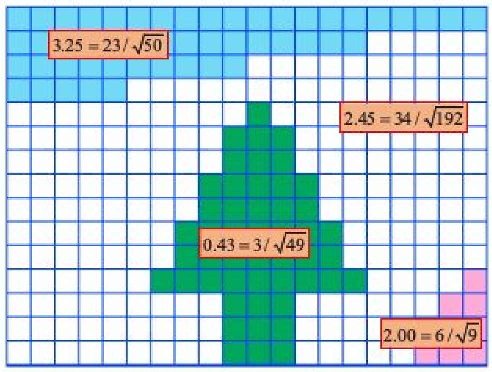
Results:

APPROACH 2:

- As the above approach is done on pixel level, it is taking a lot of computation time, so we decided to use a different approach i.e. using energy minimization technique to solve the problem.
- Here, We solve the problem from the fact that background objects are more linked to the boundary where as salient objects are not much linked to the boundary of the image.
- The image is first abstracted as a set of nearly regular superpixels using the SLIC method.
- We then construct an undirected weighted graph by connecting all adjacent superpixels (p, q) and assigning their weight $d_{app}(p, q)$ as the

Euclidean distance between their average colors in the CIELab color space.

- We further add edges between any two boundary superpixels. This is useful when a physically connected background region is separated due to occlusion of foreground objects.
- The geodesic distance between any two superpixels $d_{geo}(p, q)$ is defined as the accumulated edge weights along their shortest path on the graph.



- So, we give the measure to the saliency through following idea:

    - Here, we use the below ratio to measure saliency,

$$BndCon(p) = \frac{Len_{bnd}(p)}{\sqrt{Area(p)}}$$

Area(p) is the area of the superpixel p

$$d_{geo}(p,q) = \min_{p_1=p,p_2,\ldots,p_n=q} \sum_{i=1}^{n-1} d_{app}(p_i, p_{i+1}) \quad (2)$$

For convenience we define $d_{geo}(p,p) = 0$. Then we define the "spanning area" of each superpixel p as

$$Area(p) = \sum_{i=1}^{N} exp(-\frac{d^2_{geo}(p,p_i)}{2\sigma^2_{clr}}) = \sum_{i=1}^{N} S(p,p_i), \quad (3)$$

where N is the number of superpixels.

Where, length of a superpixel p is the length along the boundary.

$$Len_{bnd}(p) = \sum_{i=1}^{N} S(p, p_i) \cdot \delta(p_i \in Bnd)$$

We minimize the below non-linear function,

$$\underbrace{\sum_{i=1}^{N} w_i^{bg} s_i^2}_{\text{background}} + \underbrace{\sum_{i=1}^{N} w_i^{fg} (s_i - 1)^2}_{\text{foreground}} + \underbrace{\sum_{i,j} w_{ij} (s_i - s_j)^2}_{\text{smoothness}}$$

Where,

$$w_i^{bg} = 1 - exp(-\frac{BndCon^2(p_i)}{2\sigma^2_{bndCon}})$$

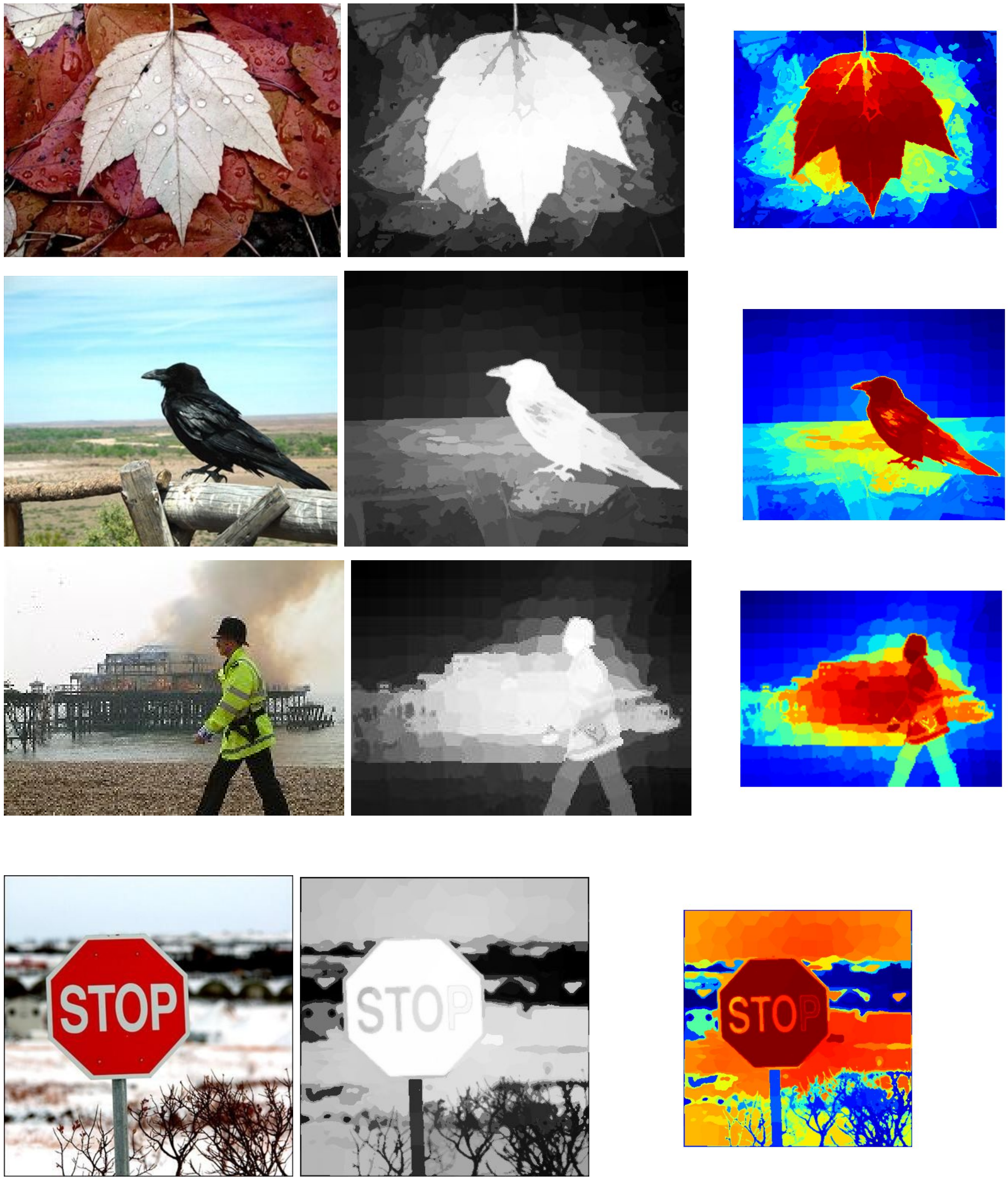
$$w_{ij} = exp(-\frac{d^2_{app}(p_i, p_j)}{2\sigma^2_{clr}}) + \mu$$

$$wCtr(p) = \sum_{i=1}^{N} d_{app}(p, p_i) w_{spa}(p, p_i) w_i^{bg}$$

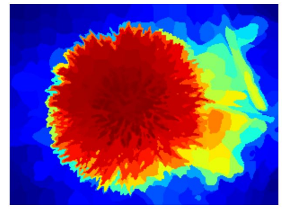
$$w_{spa}(p, p_i) = exp(-\frac{d^2_{spa}(p, p_i)}{2\sigma^2_{spa}}). \quad d_{spa}(p, p_i)$$

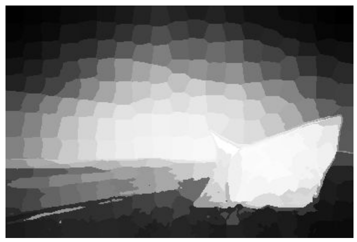
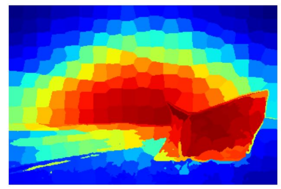
Here, wCtr is background weighted contrast, which is equivalent to w^{fg} .

Results:

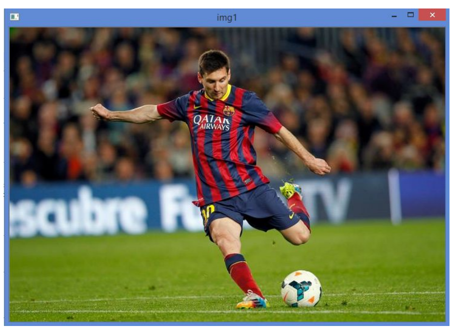
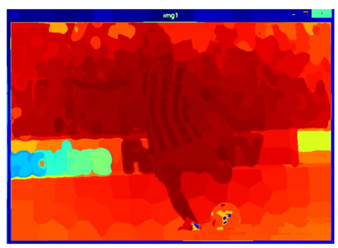


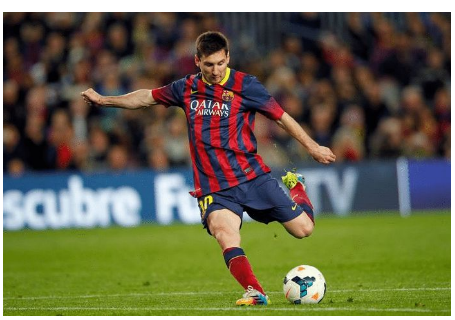
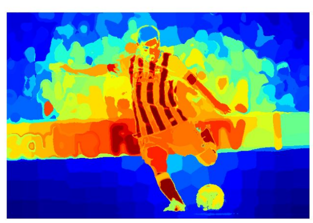




Failures of Approach-2:

- In the first image, it contains the blue border, so using this approach, it considers that entire image is distinct with border, so everything is considered as salient.
- As we can see, the second image doesn’t have blue border, so we are getting good detection of features.

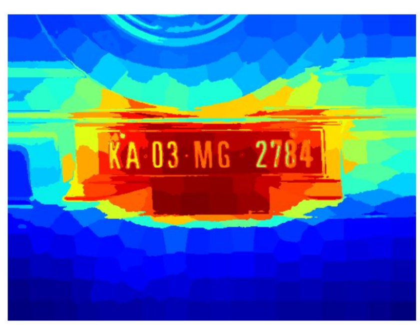
ANALYSIS:

	Approach-1	**Extension**
Abstraction	0.55301452 s	--------------
Uniqueness	0.009122849 s	0.1385328 s
Distribution	0.01104879 s	77.074188 s
Saliency	0.01099658 s	6.2409470 s

	Approach-1	**Extension**	**Approach-2**
Total Time	0.58 s	83.3974419 s	7.242528

SLIC	**Using Inbuilt**	**Coded** (For 5 iter's)
Time Taken	0.2575693 s	21.516971 s

Applications: (Number plate detection)



Citations:

- ★ Main Paper:- http://www.philkr.net/papers/2012-06-01-cvpr/2012-06-01-cvpr.pdf
- ★ Second Paper:- https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=6909756
- ★ Dataset: http://saliencydetection.net/dut-omron/