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Bayesian saliency using the spectral form of Relaxation aid cuts

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ABSTRACT

In the form of this simple formula has been extended to allow modeling of the differences and many Priors. The new framework in a form easily integrated into a training set.In proposed system, a group of local features are submitting sparse subspace collection system and to compute the saliency map of rough bumps on the front part of the study results are superpixels. The feature of Bayesian saliency for each pixels the observation likelihood based on the use of visual of shape based images assume that the hull to compute. Our state-of-art algorithms that work in the favor of comprehensive tests in a large data set the protrusion of the Bayesian model based saliency cuts.

INTRODUCTION

The term digital image refers to processing of a two dimensional picture by a digital computer. In a broader context, it implies digital processing of any two dimensional data. A digital image is an array of real or complex numbers represented by a finite number of bits. An image given in the form of a transparency, slide, photograph or an X-ray is first digitized and stored as a matrix of binary digits in computer memory. This digitized image can then be processed and/or displayed on a high-resolution television monitor. For display, the image is stored in a rapid-access buffer memory, which refreshes the monitor at a rate of 25 frames per second to produce a visually continuous display.

Normalized cuts is an efficient graph theoretic segmentationmethod robust to noise and outliers, and is thus a goodcandidate for medical imaging segmentation. Previously, ithas been used for segmentation of the spinal vertebrae and clustering of white matter fiber tracts among others.Although normalized cuts has not become as popular in themedical segmentation field as other methods such as level sets or graph cuts due to the difficulty and limitation to addprior knowledge, it has been widely used for natural imagesgiving promising results.The prior can provide valuable information combined withlow level cues (e.g., similarity of pixel brightness, color,texture and motion) to guide the segmentation to extract anobject of interest from an image. There are some techniquesto incorporate prior knowledge into normalized cuts but they are still limited.

SALIENCY PROCESS

The saliency measure, being closely related to how I perceive and process visual stimuli, usually results in a mapwhere each value describes how the pixel stands out fromits surroundings in the image. Viewed from the informationprocessing perspective, these algorithms can be categorizedinto bottom-up (stimuli-driven) or top-down (goal-oriented)approaches. Top-down saliency measure is concerned witha specific object class and the map indicates where theirImage segmentation has started to play one of the most fundamental roles in diagnosis and treatment of diseases as the new medical imaging technologies progress.Image saliency is a simulation of visual saliency, a process where observers direct gazes toward regions that attracts the most attention. In the visual attention theories, human's attention usually contains two stages, the bottom-up process and the top-down process.

They lead to two major categories of saliency detection:

bottom-up approaches focus on low-level features like color, orientation and texture from pixels or superpixels and the top-down approaches utilize mid-level or high-level cues to like face detection.

IMAGE PROCESSING FUNDAMENTAL

Digital image processing refers processing of the image in digital form. Modern cameras may directly take the image in digital form but generally images are originated in optical form. They are captured by video cameras and digitalized. The digitalization process includes sampling, quantization. Then these images are processed by the five fundamental processes, at least any one of them, not necessarily all of them.

IMAGE PROCESSING TECHNIQUES

This section gives various image processing techniques

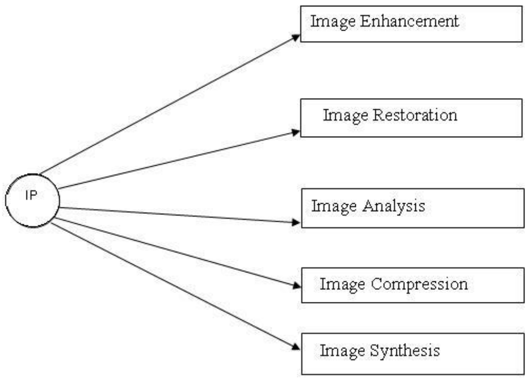


FIG: IMAGE PROCESSING TECHNIQUES

These problems with a shape based model by exploiting the shape based cues to generate maps on the center surround principle. First,compute the interest points for a coarseregion estimation of the salient object. The prior map of theproposed bayesian saliency model is computed based on thecoarse saliency region and our sparse subspace clustering method. In contrast to which measures saliency withcontrast between scanned windows and surrounding regions. In this formulation is more efficient and effective by exploitingmid level cues and better metrics. Here clustering methodextends the sparse subspace clustering by introducing aregularization term with a laplacian matrix at the superpixelLevel.

Biomedical image segmentation has started to playone of the most fundamental roles in diagnosis and treatment of diseases as the new medical imaging technologies progress. However, medical segmentation is still challenging

due to limited image contrast, presence of noise and variations in anatomy and pathology.

To alleviate these issues, prior knowledge is integrated into the segmentation method giving more robust results. In general, due to the specificity of the prior, numerous methods have been developed to solve specific case. We present a novel method to integrate shape prior knowledgeinto normalized cuts. The proposed method seeks thenormalized cut while maximizing the association of the priorwithin a group and the disassociation with the other. Ourmain contribution is that the prior is included in the costfunction without the inclusion of hard constraints avoidingthe issues described above [10].

Furthermore, depending onthe application, the method does not require the inclusion ofspatial relationships, because they are already in the prior termand it can be extended easily to deal with multiple priorsapplying Principal Component Analysis (PCA). The SpectralRelaxation of the problem provides an efficient solution, although the resulting eigenproblem is not sparse. The resultsof the proposed method are very promising even when theimage is noisy with limited contrast or the prior is inaccuratewhereas most of the previous methods require a reliable prior.This paper is an extension of our previous work in [12]including a more detailed methodology and more experimentsto verify the algorithm. We also adapt it on natural imagesand compare it with the latest methods in normalized cutswith prior. This paper is organized as follows: In the followingsection we introduce the theory behind normalizedcuts and propose our idea of how to incorporate the priorinto the formulation. We show how the formulation is madecomputationally tractable by spectral relaxation, which leadsto a non-sparse but still

efficient implementation. In section, we demonstrate our approach on two biomedical datasetsand one dataset consisting of natural images of people as wellas standard images in computer vision to make the comparison

SCOPE OF THE PROJECT

The most important ones are the prior map and clustering with super pixels. It show some prior maps generated with evaluation against other methods.

The other color interest point detectors can also be used, while it is possible to use other segmentation method. It is not clear whether additional improvements can be obtained when compared with efficient and effective mid level representations obtained in superpixels.

THEORY

In existing system, as a part of the team in front of a linear obstacle pixels that belong to a shared solution in normalized cuts. They are in a constant state impose restrictions on the dissemination of information on groups labeled by the adjoining edges and cut the shape with extra pixels in the given images.

Graph-based segmentation algorithms are based on therepresentation of an image as an undirected weighted graphwhere the pixels of the image are the nodes and the edgeshave weights that represent the similarity between nodes.A measure of similarity can be established considering pairwisepixel features like intensity, color, texture and distance.

Each edge is represented in the affinity matrix *W* that representsthe connections between nodes. The graph can bepartitioned into two disjoint sets by using the normalized cutscriterion, where the similarity among the nodes in the same set is high and across different sets is low.

Edge detection refers to the process of identifying and locating sharp discontinuities in an image. The discontinuities are abrupt changes in pixel intensity which characterize boundaries of objects in a scene. Classical methods of edge detection involve convolving the image with an operator (a 2-D filter), which is constructed to be sensitive to large gradients in the image while returning valuesof zero in uniform regions.

There is extremely large number of edge detection operators available, each designed to be sensitive to certain types of edges.

For the purpose of edge detection, gabor filter has been used. In image processing, a Gabor filter, named after Dennis Gabor, is a linear filter used for edge detection. Frequency and orientation representations of Gabor filters are similar to

those of the human visual system, and they have been found to be particularly appropriate for texture representation and discrimination. In the spatial domain, a 2D Gabor filter is a Gaussian kernel function modulated by a sinusoidal plane wave. The Gabor filters are self-similar: all filters can be generated from one mother wavelet by dilation and rotation. A set of Gabor filters with different frequencies and orientations may be helpful for extracting useful features from an image. Figure 3.2.2.1 shows the edge detected image using gabor filter.

$$G(x,y;\theta,f)=\exp\{-[(x_\theta^2 / {}_x^2)+(y_\theta^2/{}_y^2)]\}\cos(2\pi f x_\theta)$$

$$x_\theta = x\cos\theta + y\sin\theta \quad y_\theta = -x\cos\theta + y\sin\theta$$

where θ represents the orientation of the normal to the parallel stripes of a gabor function,

f represents frequency of the sinusoidal factor, is the standard deviation of guassian envelope, x and y are the corresponding axes.

As this minimum cut criterion tends to cut small sets of isolated nodes in the graph,

IMPLEMENTATION

Efficient eigenvalue solvers solely require the computation of the system matrix

$$\mathbf{A} = \mathbf{Q}^{-1/2}(\mathbf{I} - \mathbf{D}^{-1/2}\mathbf{W}\mathbf{D}^{-1/2})\mathbf{Q}^{-1/2}.$$

In our case, the computation of **A** is split into three parts: applying $\mathbf{Q}^{-1/2}$, then the ordinary graph laplacian and once again $\mathbf{Q}^{-1/2}$. As already stated above, the application of $\mathbf{Q}^{-1/2}$ can be implemented efficiently as it consists of multiplications with the low-rank matrix $\mathbf{P}0$.

EXPERIMENTAL EVALUATION

The proposed method is tested on three different kinds of datasets, two biomedical segmentation tasks and one set of natural images from the person category of the PASCAL VOC .Furthermore, we conclude the experimental evaluation with standard images (Lena and Cameraman) for illustrative purposes. The proposed method is compared with the latest techniques in constrained normalized cuts forprior incorporation such as partial grouping with normalized cuts by Yu and Shi [7] and biased normalized cuts by Maji, et al. [9]. The biased normalized cuts and the partial grouping approaches use the feature similarity term as asimilarity measure and the spatial proximity term weightedprobabilistically with the high dimensional Gaussian distribution.

The similarity between two pixels, X(i) isthe spatial location of node i, R is the neighbourhood radiusconsidered, σ is the standard deviation and F(i) is a featurevector. Our approach only uses the feature similarity term,and the spatial proximity term may be omitted as this informationis contained in the prior information. Additionally, wealso compare with the implementation of biased normalizedcuts with intervening contor cue also used in the authors'work to compute the weight matrix. The code for computingbiased normalized cuts on images is available at the authors website. All parameters are optimized manually for all approaches.

The currently in the low and mid of pixel references to the use of Bayesian saliency model is proposed as an efficient and effective. The all benchmarks based on our Bayesian formula and based on the pixels of the points of interest include rugged areas that the current accounting protrusion found that pixel level instructions. Next, distribution superpixels and rugged protrusion areas are estimated based on a novel set of pixel notes reflect. Finally, in areas rugged protrusion Bayesian visual saliency map of the center and surround is calculated on the basis of the principle of opportunity to get the accurate shape based cuts in the given image

Segmentation of people

To demonstrate the performance of our idea on natural images we employed a category of the PASCAL VOC where a ground truth segmentation is available and an automated method exists to get a prior that can be used during segmentation. We found the person category of the PSACAL VOC dataset as an ideal playground and used so called poselets for detection and generation of the prior. Poselets capture parts of a pose and the key idea is to find which poselets are tightly clustered in both appearance of image patches and configuration space of keypoints. The implementation of the poselets and annotations for training are kindly provided by the authors. One output of the poselet approach is a probability map for the presence of person in the scene, the region of interest is automatically defined around the output of the poselet object detector.

Segmentation of myocardium with our method.

MODULES COARSE SALIENCY REGION DETECTION VIA INTEREST POINTS

Both grayscale and color channels to exploit the gradient information using color information and the saliency measure of interest point detectors may be sensitive to background noise. Color image points in the key areas identified in the corners or the Harris operator to the point.

Provide useful information on spatial visual saliency points and interesting material. Eliminate those near the border of the image and the main points of all the rest to calculate a convex hull. The main object of the invention is usually around points of interest, in this method provides a rough estimation.

EVALUATION OF CONVEX HULLS AND CLUSTERING ALGORITHMS

The average number of detected points

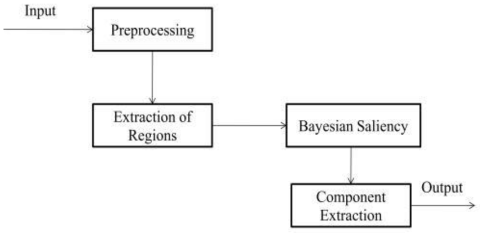
and the opinion of the images used to extract and remove the image border near real departure points for each image. Pointof interest and the fact have labeled the ground in the main part of the convex hull of an action. Than the average rate have the convex hullof the main items to provide better estimates. Used to calculate the saliency map, we decided to set up. It is an important step in our method, evaluated the results using other collection methods. Accurate plot curves back, determine whether or not the key to adjust the position of a pixel.

EVALUATION OF SALIENCY MAP MODELS

In terms of regional saliency calculating the odds of the same color space it is well short of highlighting key issues. Saliency maps are better able to evaluate the high pixel count objects in cluttered background. It can be found in the main part of the strong relative saliency maps effectively. The maps of our main areas of our return to the protrusion of the lower values, the model is very accurate and responsive high.

BLOCK DIAGRAM

The Block diagram for rain streak removal method



TECHNIQUE OR ALGORITHM

Bayesian saliency model:

An efficient and effective Bayesian saliency model using low and mid level cues. We first present the basic notations of our Bayesian formulation and then a method for coarse estimation of saliency regions based on the convex hull that includes all the detected interest points from low level cues. Next, the prior distribution is estimated based on a novel clustering algorithm with mid level cues represented by superpixels and coarse saliency regions. Finally, the observation likelihood is computed based on the center-surround principle with coarse saliency regions and thus the Bayesian visual saliency map for an image.

Input: A set of data points $\mathbf{Y} \in \mathbf{R}^{m\times n}$, and the number of desired clusters k.

1. Solve the l_1- minimization problem (1) to get the collection of c_i.
2. Form an affinity matrix $A=|C|^T+|C|$, where $C=[c_1,c_2,\ldots.c_n]$.
3. Construct a Laplacian matrix $L=I-D^{-1/2}AD^{-1/2}$ using A, where $D=diag\{d_i\}$ with $d_i=\sum_{j=1}^{n} A_{ij}$.
4. Obtain eigenvector matrix $V\in R^{n\times k}$ which consists of the first k normalized eigenvectors of L corresponding to its k smallest eigenvalues.
5. Get the segmentations of the data by performing k-means on the row of V

Output: The cluster assignments of Y

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Segmentation of color images using the poselet object detector output as the proposed approach

RESULTS & DISCUSSION

The performance over several data sets that are widely used in previous works there is a large variation amongimages including natural scenes, animals, indoor, outdoor, etc.This data set is a collection of salient objectboundaries based on the Berkeley segmentation data set. The regional contrast descriptor is the least important. The reason might be that it is a local contrast descriptor and less important comparedwith the regional background descriptor which isin some sense non-local. In the property descriptor,the geometric features are ranked higher as salient objects tend to lie in the center in most images.

The object detection problem using discriminative regional feature integration approach and the success of our approach stems fromtwo key factors. One is that we learn to integrate a lotof regional descriptors to compute the saliency scores,rather than heuristically compute saliency maps fromdifferent types of features and combine them to get the normalized cuts.

Matlab is a program that was originally designed to simplify the implementation of numerical linear algebra routines. It has since grown into something much bigger, and it is used to implement numerical algorithms for a wide range of applications. The basic language used is very similar to standard linear algebra notation, but there are a few extensions that will likely cause you some problems at first.Clustering results to calculate the saliency map as this is an important step our system uses the results of the evaluation of the other clustering methods.

CONCLUSION

Finally, the Bayesian framework using a saliency model of visual cues in the low and mid-level for information saliency points that does not entail a complete scan windows or the introduction of a means test based on the right side. In addition, we use a sparse representation of the superpixel level and propose a new image clustering method and apply it to calculate the distribution of the bulge. Saliency map model and the experimental results demonstrate the effectiveness of our clustering method. Create a discriminatory manner and also to bring back to our state-of-the-art saliency maps is more accurate than method

APPENDIX

ANNEXURE I

% The quasi-invariant derivatives can be used to suppress undesired edges

% such as shadow, shading and specular edges.

% LITERATURE:

% J. van de Weijer, Th. Gevers, A.W.M Smeulders

% " Robust Photometric Invariant Features from the Color Tensor"

% IEEE Trans. Image Processing,

% vol. 15 (1), January 2006.

% example of photometric invariant edge detection

% fig 1: input image

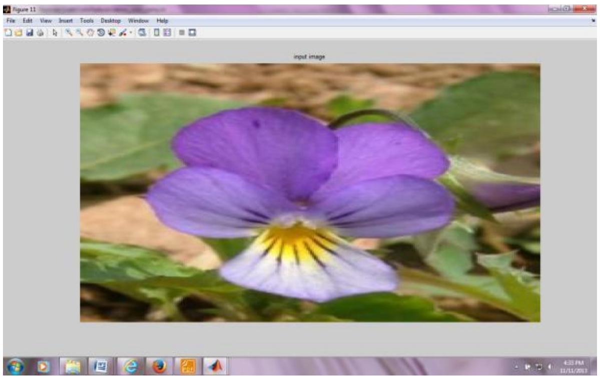
% fig 2: all edges

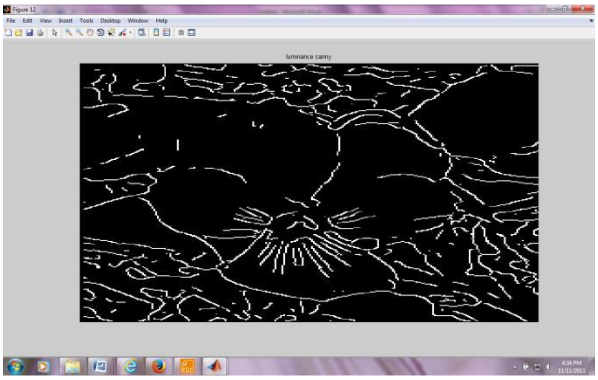
% fig 3: no shadow and shading edges

% fig 4: no specular edges (highlights)

% fig 5: no shadow-shading and specular edges (only material edges)

ANNEXURE II

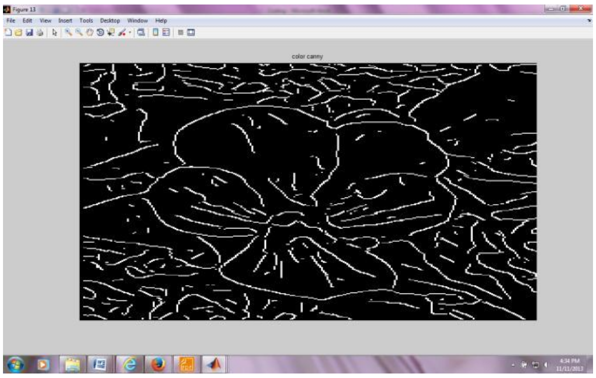




```
n = imread('speelgoed.tif'); % test image
=1;                          standard deviation
n derivative kernel
=3;                          standard deviation
n averaging kernel
3;                           reshold on which edges
ay
```

[out0]=co

lor_canny(input_im, sigma1, sigma2, 0); [out1]=color_canny(input_im, sigma1, sigma2, 1); [out2]=color_canny(input_im, sigma1, sigma2, 2); [out3]=color_canny(input_im, sigma1, sigma2, 3);

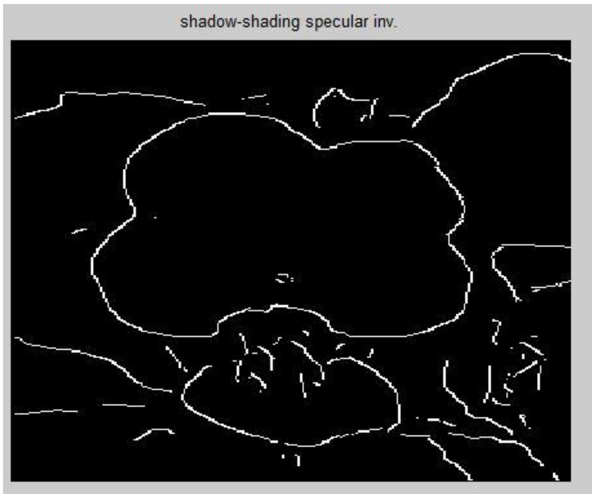


```
figure(1);
imagesc(input_im);
title('input
image');axis off;

figure(2); colormap(gray);
imagesc(out0>edgeT); title('color
gradient');axis off;

figure(3); colormap(gray);
imagesc(out1>edgeT);
title('shadow-shading inv.');axis off;

figure(4); colormap(gray);
imagesc(out2>edgeT);
title('specular inv.');axis off;
```



```
figure(5); colormap(gray);
imagesc(out3>edgeT);
title('shadow-shading specular
inv.');axis off;

% example of isoluminance : edges are
lost in the transformation to luminance
% fig 11: input image

% fig 12: luminance canny (not all
edges of the flower are detected)
% fig 13: color canny

input_im=imread('
flower.jpg');
sigma1=2;
sigma2=2;

flower1=color_canny(input_im,
sigma1,sigma2, 0);
flower2=canny(RGB2luminance(input
_im), sigma1); figure(11);

imagesc(input_im);title('input
image');axis off; figure(12);

colormap(gray);
imagesc(flower2 > 5);
title('luminance canny');axis
off; figure(13);
```

```
colormap(gray);
imagesc(flower1 > 5);
title('color canny');axis off;
```

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