TIGER: A TEXTURE-ILLUMINATION GUIDED ENERGY RESPONSE MODEL FOR ILLUMINATION ROBUST LOCAL SALIENCY

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Abstract

• A novel texture-illumination guided energy response (TIGER) model for illumination robust local saliency is proposed.
• Local saliency is quantified by a modified Hessian energy response guided by a weighted aggregate of texture and illumination components from an image.
• Higher correlation between local saliency maps constructed from the same scene under different illumination conditions can be achieved.

Background Information

• Local saliency detection is necessary in a variety of computer vision and image processing tasks.
  • Point/Object Tracking
  • Object recognition
  • Keypoint detection
  • Content based image retrieval
• Common approaches for local keypoint detection include:
  • Laplacian of Gaussian (LoG) response [1]
  • Difference of Gaussians (DoG) response [2]
  • Hessian-based response model [3]
• A local saliency model that is robust to varying illumination conditions is highly desirable for image processing and computer vision tasks.
  • Spatially varying illumination conditions poses problems in current state of the art.
  • Local saliency detection under varying illumination is not well explored.
• Existing illumination robust local saliency techniques are greatly dependant on the scene.

Experimental Setup

A total of 49 images across 10 different scenes were tested.

Datasets used:
  • ViCS (Self recorded)
  • Select from Yale Face II [4]
  • GTILT [5]
  • AMOS [6]
• Algorithms tested:
  • TIGER
  • Laplacian of Gaussian (LoG) [3]
  • Difference of Gaussians (DoG) [2]
  • Hessian [3]

Methods

TIGER Local Saliency Model

In Hessian-based approaches, the Hessian matrix, $\Phi$, is used to quantify local saliency at each pixel.

$$\Phi(i) = \left( \begin{array}{c} \Delta x L(i) \\ \Delta y L(i) \\ \Delta x^2 L(i) \\ \Delta y^2 L(i) \\ \Delta xy L(i) \end{array} \right)$$

where $\Delta x$ represents a gradient in the x direction, $\Delta y$ and $\Delta xy$ are gradients in the x and y directions, respectively. We model the image, $I$, as an additive composition of texture, $T$, and illumination, $L$.

$$I = T + L$$

A modified Hessian matrix, $\Phi_q$, can thus be produced as

$$\Phi_q(i) = \left( \begin{array}{c} \Delta x^2 (T + L) + \Delta xy (T + L) \\ \Delta (T + L) \\ \Delta y^2 (T + L) \end{array} \right)$$

where $\alpha$ and $\beta$ are empirically determined constants. Local saliency, $s$, is determined as

$$s = \Phi_q(i)$$

By repeating this process for each pixel within an image, $I$, a local saliency map is produced.

Bayesian Disassociation

To produce the modified Hessian matrix described in Eq. 1, $T$ and $L$ are required.
• Produce an estimate of $L$ (denoted as $\hat{L}$).
• Approximate $\hat{T}$ as the residual between $I$ and $\hat{L}$, i.e., $\hat{T} = I - \hat{L}$.

We formulate the estimation of $L$, as a Bayesian least-squares minimization problem:

$$L = \arg\min L(E(L)|L) = \arg\min \left( \sum_i (E(L_i)-L_i) \right)$$

where $E(L)$ denotes the expectation. This equation can be solved as

$$L = \int L(p(L|E))$$

Posterior Probability Estimation

The posterior probability, $p(L|E)$, is required to solve the Bayesian minimization.
• Unknown and difficult to obtain analytically.

For this reason, a non-parametric Monte Carlo sampling approach is used [7]:
• GOAL: Establishe a set of pixels, $\Omega$, within a region, $q_i$, surrounding the pixel of interest, $q$.
  • Uniformly sample from $\Omega$ with equal probability.
  • Likelihood of accepting the 4th pixel into $\Omega$ is based on an acceptability probability, $\gamma(q_i)$.

Estimate $p(L(q))$ as a weighted histogram of all pixels in $\Omega$.

$$\gamma(q_i) = \exp\left( \sigma - \frac{1}{\sqrt{2\pi}} \left( \sum_{i=1}^n \frac{||L_i - E(L)||}{\sigma} \right) \right)$$

and the weighted histogram is calculated as

$$p(L) = \frac{\sum_{i=1}^n \gamma(q_i)(L_i - E(L_i))}{\sum_{i=1}^n \gamma(q_i)}$$


References


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