Active contour model driven by local histogram fitting energy

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A brief introduction and an overview of the presentation

Some context

Active contour model **(ACM)** are a very popular image segmentation technique. They are heavily used in many applications such as image processing and computer vision. The basic idea is to evolve a closed curve so as to minimise a given energy functional. The evolving curve will stop converging when the energy functional reaches its minimum through a descent method.

Admitting the **(ACM)** can be categorised to two major classes: edge-driven and region-driven. Edge driven methods can locally stop the evolution when the evolving curve reaches a high gradient. However, their resistance to noise is still quite limited. It is possible to make them better by choosing an appropriate flow term to enlarge the capture range.

Region-driven **(ACM)** utilize more global information for segmentation using distributions of intensity or texture in the regions. Therefore, these methods are robust to noise and furthermore able to segment objects with weak boundary or even without edge, provided an initial estimation can be given.

Preview of the contents of the paper

In this paper, a non parametric local region-based **(ACM)** driven by local histogram fitting energy is introduced. A local histogram fitting energy functional is constructed with a proposition of distances are defined to decide whether the current kernel width is appropriate, the kernel (a Gaussian) is used inside the energy. The novelty is that the paper introduces local histogram based **(ACM)**. Some experimental results are presented.

A brief synthesis of the presented topics/papers

The basic idea: Strike a balance between local and global features Construct a local fitting energy in a local region confined by a kernel function.

Local histogram fitting energy

Using a Gaussian Kernel: $K_\sigma(d) = c\ exp(-\frac{d^2}{2\sigma^2})\mathbb{1}_{[-\rho,\rho]}$, where c is a normalizing constant. ρ is the kernel width which defines the size of Gaussian mask, usually $\rho = 2\sigma$. The local histogram fitting energy:

$$E^{LHF}(\vec{C}, P^i, P^o) = \int_{\Sigma^{in}} K_\sigma(x-y) D_{L1}(P_i^x, P_r^y)dx + \int_{\Sigma^{out}} K_\sigma(x-y) D_{L1}(P_o^x, P_r^y)dx$$

The local histogram fitting energy is a weighted distance of the local histogram P_r^y to the fitting histogram P_i^x and P_o^x with K_σ as the weight assigned to each local histogram P_r^y at y. The weights are dominated by the distance between x and y.

Level set formulation

Using the level set function to implicitly model the evolution of the curve:

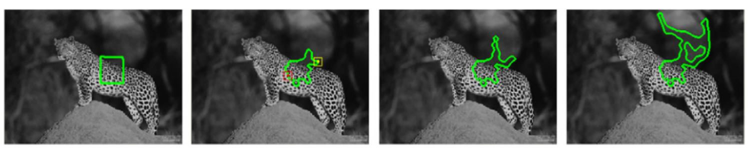
$$\begin{aligned} E_x^{LHF}(\phi, P_i^x, P_o^x) = & \int_\Omega H(\phi) K_\sigma(x-y) \int_0^R |P_i^x(z) - P_r^y(z)| dz dy \\ & + \int_\Omega (1 - H(\phi)) K_\sigma(x-y) \int_0^R |P_o^x(z) - P_r^y(z)| dz dy \end{aligned}$$

Where H is the heaviside step function.

GOAL: minimize the local histogram fitting energy for all of the points in the whole image domain. Thus, the total energy is defined by:

$$E(\phi, P_i^x, P_o^x) = \int_\Omega |\nabla H(\phi(x))| dx + \lambda \int_\Omega E^{LHF}(\phi, P_i^x, P_o^x) dx$$

Problem with the proposed method for now : The various parts of the evolving curve may evolve independently.



→ The yellow and red pixels compute their histogram independently (local fitting histograms), which are irrelevant to the object.

⟹ Varying the kernel width. An effective implementation with a supplementary set of input parameters yields satisfactory results.