Energy functions can be used to create thousands of pairs.
Optimization is made much faster.

What is an Energy Function?

$E(x, y)$, measures the “quality” of combination of input $x$ and output $y$:

$E(x, y) = y^T L y + \lambda (y - x)^T (y - x)$

$x$ - input signal
$y$ - output prediction
$L$ - matrix enforcing smoothness

For an optimal $y$, simply minimize $E(x, y)$ given the input, $x$:

$y_{opt} = \arg\min_y E(x, y)$

Energy functions can be used to create thousands of pairs for supervised learning, BUT:

Motivation

Supervised Training is Expensive/Impossible

Semantic Segmentation

Optical Flow Estimation

Medical Imaging

Single-Image Dehazing

We propose an unsupervised training methodology, relying on energy functions.

Our Approach

Train the network such that its prediction minimizes an unsupervised energy function:

$E(x_i, \theta) = \arg\min_{\theta} \sum_{i} E(x_i, y_p(x_i, \theta))$

Once training is over, prediction can be made much faster.

Application I: Seeded Segmentation

Goal: recover pixelwise semantic labeling from partial human-provided seeds/scrribbles

Model the image using a graph:

Each edge has a weight:

$w_{ij} = exp^{-||d_{ij}||^2}$

Graph Laplacian Matrix

$E = \sum (y^T L y + \lambda (y - x)^T Q (y - x))$

Random Walker Energy Function [1]

$x^T \in R^N$ - output probability for class $i$
$L \in R^{N \times N}$ - graph Laplacian matrix
$Q \in R^{N \times N}, Q_{ii} = '1' \ if \ seed, \ '0' \ else$

Application II: Single Image Dehazing

Goal: given a hazy image, recover the clear-day scene radiance

Each pixel in the image is a combination of the clear scene radiance, and the atmospheric “airlight”

$\hat{I}(x) = 1 - \omega \cdot min_{y \in \mathcal{Y}} \frac{I^*(y)}{A^T}$

Using DCP, one can calculate $\hat{I}(x)$

$\hat{I}(x)$ is refined by minimizing the soft matting energy:

$E(t, \hat{t}) = t^T L t + \lambda (\hat{t} - t)^T Q (\hat{t} - t)$

DCP - Dark Channel Prior [2]

Within a small image patch in a natural outdoor image, the darkest pixel of all channels $\rightarrow 0$

$l_{dark}(x) = \min_{c \in \mathcal{C}_{rgb}} \min_{y \in \mathcal{Y}} (I^*(y)) \rightarrow 0$

$L$ - matting Laplacian, $N = \#$ of pixels, $[p_a]$ - patch size, $\mu_a, \Sigma_a$ - patch (mean,var), $\epsilon$ - regularization, $D_\mu$ - identity

Motivation: given intensity $I(x)$, recover the clear-day scene radiance $\hat{I}(x)$.

Deep Energy – Unsupervised Training of Deep Neural Networks

Alona Golts

1Department of Computer Science, Technion, 2Google Research Haifa

Reference
