

1 Non-parametric Model for Background Subtraction

Authors: Ahmed Elgammal, David Harwood, Larry Davis

Method Summary:

- **Basic Background Model:** Probability density function with a kernel $Pr(x_t) = \frac{1}{n} \sum_{i=1}^N K(x_t - x_i)$ computed from recent sample of intensity values. K is chosen to be normal function. Thus, it is a non-parametric model and claimed to be superior to mixture of K gaussians
- **Suppress False Detections:** False Detections could be due to random noise which should be homogeneous or small movements which should be spatially clustered. Assuming consecutive frames can have only small displacements of pixels, detect if a pixel caused by movement of background object in small neighborhood of the detection. Pixel displacement probability and in turn connected component displacement probability are computed and thresholds are set.
- **Shadow Detection:** $s = R + G + B$ is used as lightness measure. Set reasonable bounds on ratio of value of s in a static background frame to that in the current frame
- **Background model updation:** Short term and long term models of background are computed and their intersection is taken.
- **Spatial Coherency:** Morphological operators.

Key Idea: Non parametric model formulation.

Advantage: Overcomes limitations of Mixture of Gaussians model, like low detection sensitivity or adaptations to targets.

Disadvantage: Too many parameters to tune.

2 Bayesian Modeling for Dynamic Scenes

Authors: Yaser Sheikh, Mubarak Shah

Method Summary:

Unlike the previous paper, both the foreground objects and background are modeled. The paper outlines three principles:

- **Spatial correlation:** Unlike the previous paper assumes that intensities of pixels are not independent but they correlated. So, this paper represents background using a single function. This model is a function of five variables : r, g, b, x and y. It uses Kernel Density Estimation technique like the previous paper for the learning this model.
- **Temporal Persitence:** Interesting objects tend to remain in spatial vicinity and tend to maintain consistent colors from frame to frame. Foreground objects are modeled as a mixture of uniform and Kernel function.
- **Spatial Context:** To remove the artifacts, generally morphological operators are used. This paper however, proposes Markov Random Field formulation to remove the inconsistencies, making use of the fact that objects in the real world tend to be spatially coherent. s-t cuts are used to solve the optimization problem of MAP for the MRF.

Key Idea: Modeling both foreground and background, and outlining three new principles: spatial correlation, temporal persistence, spatial context.

Advantage: Principled approach.

Disadvantage: Complex as compared to previous approaches like Mixture of Gaussians.