KERNEL SELECTION FOR MEAN SHIFT BACKGROUND TRACKING IN VIDEO SURVEILLANCE

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Abstract: Nonparametric kernel density estimation has been successfully used in modeling the background statistics, in video surveillance, due to its capability to perform well without making any assumption about the form of the underlying distributions. To overcome the heavy computational load of the method, we recently proposed a fast approach based on a tracking mean shift estimator. In this paper we study the kernel selection problem for the mean shift background tracker. Comparative results for the Gaussian and Epanechnikov kernel are included.

Keywords: Background subtraction, motion segmentation, tracking, nonparametric kernel density estimation, video surveillance.

1. INTRODUCTION

Visual surveillance is a rapidly growing field [5], with considerably increased interest since the latest terrorist incidents [1]. The overall reliability of the system heavily depends on the accuracy and robustness of the estimated background. We describe here an efficient background estimation method proposed in our previous work [6], based on mean shift tracking, then we address the problem of kernel profile selection for optimized performance of the tracking estimator.

Background is commonly modeled at pixel level, as a random vector with an associated probability density function (PDF). The unknown density functions can be represented parametrically [7], or nonparametrically [3]. Given a sample of N data points, $\mathbf{x}_i$, drawn from a distribution with multivariate probability density function $p(\mathbf{x})$, a nonparametric kernel estimate of this density at $\mathbf{x}$ can be written as:

$$\hat{p}(\mathbf{x}) = \frac{1}{N}\sum_{i=1}^{N} K_h(\mathbf{x}-\mathbf{x}_i)\,, \tag{1}$$

where K_h is the kernel function with scale parameter h and the estimated background is

$$\mathbf{b} = \arg\max_{\mathbf{x}_k} \hat{p}(\mathbf{x}_k). \qquad (2)$$

The computational complexity is O(N^2) for a direct implementation but, can be reduced to O(2N) by using Fast Gauss Transform, data clustering and clever data structures [4].

2. EXPERIMENTAL RESULTS AND DISCUSSION

By combining strong points from parametric, nonparametric and histogram based density estimation methods, our fast background tracking technique obtains complexity O(N^0). A concise pseudo-code description of the background tracking algorithm for a given spatial location is given in Figure 1.

```
if( K_h(x_new — b) != 0 )
        update( b and p̂(b) );
        else if( Hist(x_new) > threshold )
                if( p̂(x_new) > p̂(b) )
                        b =: x_new;
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Fig. 1. Pseudo code description of the fast background tracking algorithm.

When a new data point falls within the domain of the kernel function, the background color is updated using the following rule:

$$\mathbf{b}_{new} = (1-\alpha)\mathbf{b}_{old} + \alpha\mathbf{x}_{new}\, g\left(\frac{\| \mathbf{x}_{new} - \mathbf{b}_{old} \|}{h}\right), \qquad (3)$$

with α a small positive constant, acting as a learning rate and $g()$ is the derivative of the estimator kernel profile. The theoretical motivation behind this option is related to the mean shift paradigm [2]. In the present work, we compare the results obtained by the tracking mean shift background estimator for two of the most commonly used kernels: the Epanechnikov kernel and the Gaussian kernel

In our first experiment, we generated a constant background corrupted with zero mean white noise normally distributed between -0.5 and 0.5. We evaluated standard deviation of the estimation error obtained for the mean shift tracking estimators using Epanechnikov and Gaussian kernels, on a sequence of 200 samples with added noise. A sliding data window of N = 40 samples was used. In order to insure the same tracking range, the scale parameter h = 0.33 was used for the Gaussian kernel, truncated to a length of 3h (the scale parameter) and h = 1 for the Epanechnikov kernel, resulting in a rectangular shape for $g()$. The results of five experiments are summarized in Figure 2.

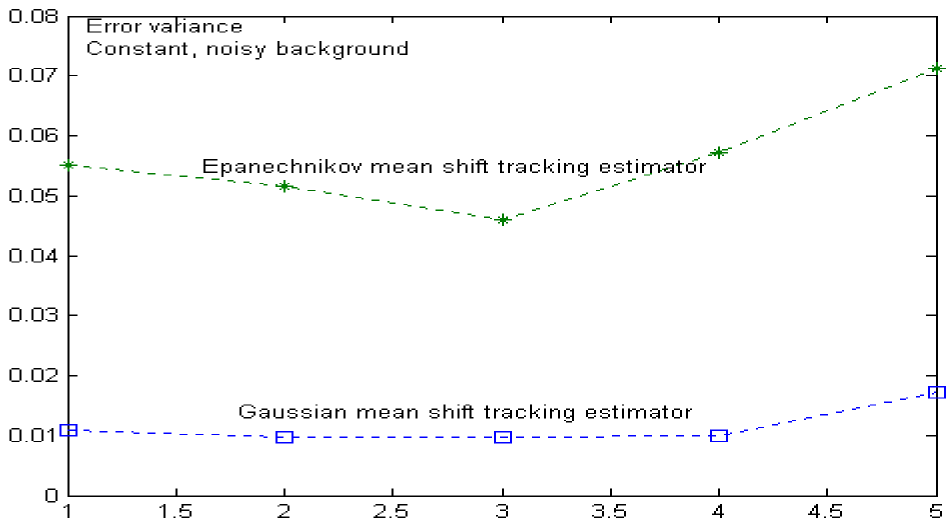

Fig. 2.

In the second set of five experiments, a step change of amplitude 0.1 with added noise as before was used to estimate the performances of the Epanechnikov and Gaussian kernels. The results are illustrated in Figure 3.

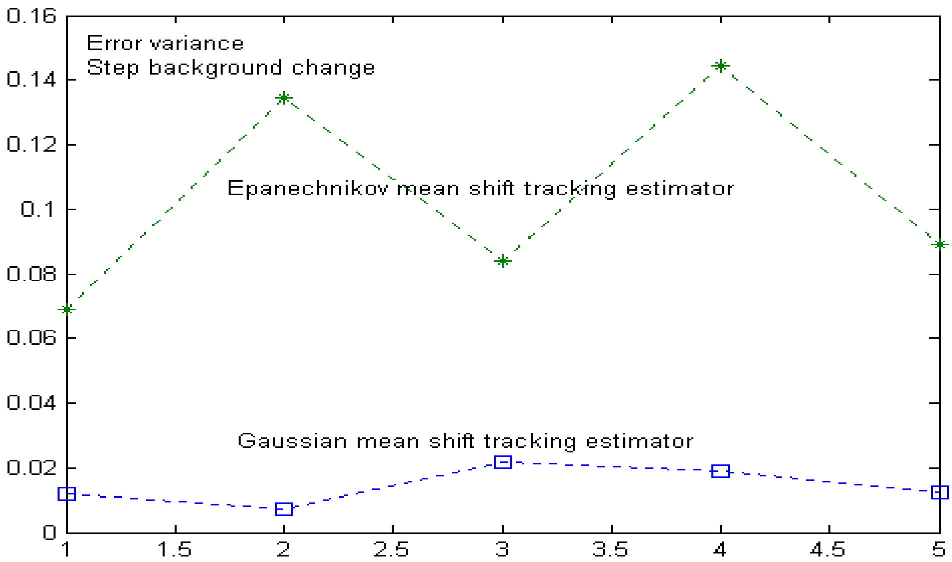

Fig. 3.

In all experiments the Gaussian kernel clearly outperformed the Epanechnikov kernel. The computational cost for the Gaussian kernel is higher with one multiplication per estimated background pixel, but still allows real time implementation. In our experiments on video data, with a 700 MHz Pentium III processor based PC, the computing time for a 352×240 image resolution and 1/16 of the background image pixels updated each frame was nearly 8 ms per frame.

3. CONCLUSIONS

We have found that, for the fast mean shift tracking background estimator proposed, the Gaussian kernel clearly outperforms the Epanechnikov kernel in terms of error variance.

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