# A comparison between contour and histogram-based observation models for tracking[1]

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## ABSTRACT

In probabilistic tracking tasks, the quality of the observation model used is of prime importance. In some models, evidence is extracted from the outline of the object while in others, it is extracted from the region bounded by this. In this article, we shall study and compare the behavior of two outline-based models with one histogram-based model.

### Keywords

Probabilistic tracking, dynamical model, observation model.

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## 1. INTRODUCTION

The use of probabilistic models applied to tracking enable us to estimate the *a posteriori* probability distribution, $p(X \mid Z)$, of the set of valid configurations for the object to be tracked, represented by a vector $X$, from the set of measurements $Z$ taken from the images of the sequence. The likelihood at a given time $t_{k-1}$ is combined with a *dynamical model* giving rise to the *a priori* distribution in the next instant $t_k$, $p(X)$. The relation between these distributions is given by Bayes' Theorem. In order to estimate $p(Z \mid X)$, know as the *observation probability*, we will use several contour-based *observation models*, define in [Bla98] [Luc03a] [Luc03b], and one region histogram-based observation model.



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## 2. OBSERVATION MODELS

### Observation model based on intensity restricticions

Let $x = f(X_{t_k}; m)$ (where $X_{t_k}$ defines the specific configuration of the object model, and $m$ is the parameter vector which associates each point within the model with a point on the image plane), a point belonging to the model outline at the instant $t_k$. Let $S$ be a neighborhood of $\boldsymbol{x}$ subdivided into $S_i$ and $S_e$ (corresponding respectively to the parts of the neighborhood which remain towards the inside and outside of the object outline), then we will calculate the expression:

$$d(c_{t_k}, m) = f(X_{t_k}; m) - f(X_{t_{k-1}}; m)$$

We then consider the optical flow constant in $S_i$ and $S_e$, respectively, and use the system of equations proposed in [Luc81] to obtain $f_{S_x} = (f_x, f_y)$, where $S_x$ shall be $S_i$ or $S_e$, respectively. The temporal derivatives of the image are computed as

$$I_t(x) = I^{(k)}(x + d(c_{t_k}, m)) - I^{(k-1)}(x)$$

Two different flow estimations are obtained, $f_{S_i}(c_{t_k}, m)$ and $f_{S_e}(c_{t_k}, m)$, corresponding to the inner and outer area of the neighborhood of x, respectively.

The quadratic differences with the expected flow (which in this case equals zero) are equivalent to the squared norm of the estimated flow vectors:

$$Z_{S_i}(c_{t_k}, m) = \left\| f_{S_i}(c_{t_k}, m) \right\|^2$$
$$Z_{S_e}(c_{t_k}, m) = \left\| f_{S_e}(c_{t_k}, m) \right\|^2$$

These values may be combined and a value of $Z(c_{t_k}, m)$ may therefore be obtained:

$$Z(c_{t_k}, m) = \frac{Z_{S_e}(c_{t_k}, m)}{Z_{S_e}(c_{t_k}, m) + Z_{S_i}(c_{t_k}, m)}$$

We will consider that the presence probability of the measurements obtained for the image, since they have been caused by the point of the outline corresponding to the vector **m** of the sample in question, defined by the vector $c_{t_k}$, must be proportional to the function $Z(c_{t_k}, m)$ computed previously, and that given the independence between the different points of the outline,

$$p(Z \mid c_{t_k}, m_i) \propto Z(c_{t_k}, m_i)$$

with $m_i$ being the vector which identifies the i-nth point on the outline of the model.

## Observation model based on histogram

Given the region occupied by the outline defined by $X_i$ i, we can calculate its histogram and define the observation probability according to the distance between this histogram and that of a reference model extracted from the first frame of the sequence. For this work, we have used one function for the observation probability:

$$p(Z \mid X_{t_k}) \propto \exp^{-\frac{d_H(H_r, H_{x_i})^2}{K}}$$

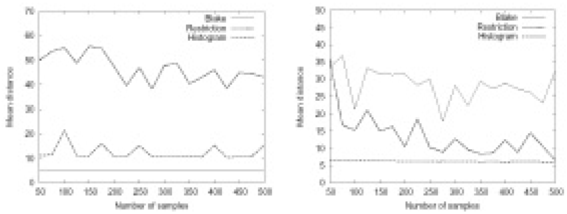
with $H_r$ being the reference histogram, $H_{x_i}$ the histogram corresponding to the sample, $K$ a constant, and

$$d_H(H_r, H_{x_i}) = \sum_j \frac{(H_r(j) - H_{x_i}(j))^2}{H_r(j) + H_{x_i}(j)}$$

## 3. EXPERIMENTS

We have used the CONDENSATION algorithm [Bla98] on two image sequences, each lasting 10 seconds, at 25 frames per second, 320x240 pixels, and 8 bits per band and pixel. These sequences correspond to the movement of a hand over a background with and without clutter. For measuring the performance of each observation model, we have used the following procedure: given the initial frame of each sequence, we have used the Harris operator to obtain a number of points, and have manually selected five points placed on the contour of the object of interest; we have then located the corresponding points for the entire sequence. Once the tracking process has finished, we compute the mean Euclidean distance between each point and the position estimated by the tracker for that point, throughout the entire sequence.

The results obtained for the first sequence (Figure 1.a) show that Blake's model is clearly superior. Nevertheless, the scene shown in this sequence is unrealistic as it has a constant background. In the case of the second sequence (Figure 1.b), the results are very different. In the presence of clutter, Blake's model behaves much worse. The intensity restriction-based observation model performs slightly better for the second sequence than for the first.




a) b)

**Figure 1. Precision obtained according to the number of samples by the different observation models for the first (a) and second (b) sequence.**

## 4. CONCLUSIONS

In this moment, the last experiments suggest that probably, the combination of different sources of evidence applied to probabilistic tracking tasks can produce better results than models applied independently.

## 5. REFERENCES

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