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著者	Sugandi Budi, Kim Hyoungeop, Tan Joo Kooi, Ishikawa Seiji
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A COLOR FEATURES-BASED METHOD FOR OBJECT TRACKING EMPLOYING A PARTICLE FILTER ALGORITHM

Budi Sugandi, Hyoungseop Kim, Joo Kooi Tan, Seiji Ishikawa
Graduate School of Engineering, Kyushu Institute of Technology
budi@kimlab.cntl.kyutech.ac.jp

Abstract

We proposed a method for object tracking employing a particle filter based on color feature method. A histogram-based framework is used to describe the features. Histograms are useful because they have property that they allow changes in the object appearance while the histograms remain the same. Particle filtering is used because it is very robust for non-linear and non-Gaussian dynamic state estimation problems and performs well when clutter and occlusions are present on the image. Bhattacharyya distance is used to weight the samples in the particle filter by comparing each sample's histogram with a specified target model and it makes the measurement matching and sample's weight updating more reasonable. The method is capable to track successfully the moving object in different outdoor environment with and without initial positions information, and also, capable to track the moving object in the presence of occlusion using an appearance condition. In this paper, we propose a color features-based method for object tracking based on the particle filters. The experimental results and data show the feasibility and the effectiveness of our method.

Keywords: object tracking, particle filter, color histogram

1. Introduction

Object tracking is an important step in many applications such as human-computer interaction, medical imaging, video compression, video surveillance and gesture recognition. The object tracking is a challenging problem due to the presence of noise, occlusion, clutter and dynamic changes in the scene other than the motion of objects of interest. A variety of tracking algorithms has been proposed and implemented to overcome these difficulties. They can be roughly classified into two categories: deterministic methods and stochastic methods.

Deterministic methods track the object by performing an iterative search for a similarity between the template and the current image. The robust similarity measures have been applied and the mean-shift algorithm or other optimization techniques have been utilized to find the optimal solution [1-2]. Model-based tracking algorithms incorporate *a priori* information about the objects to develop representations such as skin complexion, body blobs, kinematics skeleton, silhouettes or layer information [3-5]. Appearance-based approaches apply

recognition algorithms to learn the objects either in some basis such as the eigenspace formed from observations or in kernel space [6].

On the other hand, the stochastic methods use the state space to model the underlying dynamics of the tracking system. In a linear-Gaussian model with linear measurement, there is always only one mode in the posterior probability density function (PDF). The Kalman filter can be used to propagate and update the mean and covariance of the distribution of the model [7]. For nonlinear or non-Gaussian problems, it is impossible to evaluate the distributions analytically and many algorithms have been proposed to approximate them. The particle filter, also known as sequential Monte Carlo [7], is most popular approach which recursively constructs the posterior PDF of the state space using Monte Carlo integration. It has been developed in the computer vision community and applied to tracking problem and is also known as the Condensation algorithm [8].

The particle filter based tracking algorithms usually use contours, appearance models, or color features [8-10]. The contour-based methods are invariant against the illumination variation but computationally expensive which restricts the number of samples (particles) [8]. Unfortunately when the dimensionality of the state space increases, the number of samples required for the sampling increases exponentially. On the other hand, the color histogram is robust against noise, occlusion, rotation and scale invariant, and is also easy to implement [9-10].

In this paper, we employ a particle filter to track a moving object based on the color features. A target model is tracked using the particle filter by comparing its histogram with the histogram of every sample using the Bhattacharyya distance which makes the measurement matching and weight updating more reasonable.

2. Particle filter

The particle filter is a Bayesian sequential importance sampling technique, which recursively approximates the posterior distribution using a finite set of weighted samples (particles). It consists of essentially two steps: prediction and update.

Given all available observations $\mathbf{z}_{1:t-1} = \{\mathbf{z}_1, \dots, \mathbf{z}_{t-1}\}$ up to time $t-1$, the prediction stage uses the probabilistic system transition model $p(\mathbf{x}_t|\mathbf{x}_{t-1})$ to predict the posterior at time t as,

$$p(\mathbf{x}_t|\mathbf{z}_{1:t-1}) = \int p(\mathbf{x}_t|\mathbf{x}_{t-1})p(\mathbf{x}_{t-1}|\mathbf{z}_{1:t-1})d\mathbf{x}_{t-1} \quad (1)$$



At time t , the observation \mathbf{z}_t is available, the state can be updated using Bayes' rule,

$$p(\mathbf{x}_t | \mathbf{z}_{1:t}) = \frac{p(\mathbf{z}_t | \mathbf{x}_t) p(\mathbf{x}_t | \mathbf{z}_{1:t-1})}{p(\mathbf{z}_t | \mathbf{z}_{1:t-1})} \quad (2)$$

where $p(\mathbf{z}_t | \mathbf{x}_t)$ is described by the observation equation.

In the particle filter, the posterior $p(\mathbf{x}_t | \mathbf{z}_{1:t})$ is approximated by a finite set of N samples $\{\mathbf{x}_t^i\}$ ($i = 1, \dots, N$) with the weights w_t^i . The candidate of samples $\tilde{\mathbf{x}}_t^i$ are drawn from an importance distribution $q(\mathbf{x}_t | \mathbf{x}_{1:t-1}, \mathbf{z}_{1:t})$ and the weight of the samples are,

$$w_t^i = w_{t-1}^i \frac{p(\mathbf{z}_t | \tilde{\mathbf{x}}_t^i) p(\tilde{\mathbf{x}}_t^i | \mathbf{x}_{t-1}^i)}{q(\tilde{\mathbf{x}}_t^i | \mathbf{x}_{1:t-1}, \mathbf{z}_{1:t})}. \quad (3)$$

In our case, $q(\mathbf{x}_t | \mathbf{x}_{1:t-1}, \mathbf{z}_{1:t}) = p(\mathbf{x}_t | \mathbf{x}_{t-1})$ and the weights become the observation likelihood $p(\mathbf{z}_t | \mathbf{x}_t)$.

The samples are resampled to generate new unweighted particles set according to their importance weights.

3. Observation model

The observation model is used to measure the observation likelihood of the samples and is an important issue for object tracking. Many observation models have been built for particle filtering tracking. One of them is a contour based appearance template. The tracker based on a contour template gives an accurate description of the targets but performs poorly in clutter and is generally time-consuming. The initialization of the system is relatively difficult and tedious. In contrast, color-based trackers are faster and more robust, where the color histogram is typically used to model the targets to combat the partial occlusion, and non-rigidity.

3.1. Color features

This section describes how the color features is modeled in a rectangular region R , where R can be a region surrounding the object to be tracked or region surrounding one of the hypothetical regions. A color histogram is commonly used for object tracking because they are robust to partial occlusion and are rotation and scale invariant. They are also flexible in the types of object that they can be used to track, including rigid and non-rigid object.

The color distribution is expressed by an m -bins histogram, whose components are normalized so that its sum of all bins equals one. For a region R in an image, given a set of n samples in R , denoted by $\mathbf{X} = \{x_i, i = 1, 2, \dots, n\} \in R$, the m -bins color histogram $H(R) = \{h_j\}$, ($j = 1, 2, \dots, m$) can be obtained by assigning each pixel x_i to a bin, by the following equation:

$$h_j = \frac{1}{n} \sum_{(x_i) \in \mathbf{X}} \delta_j[b(x_i)]. \quad (4)$$

Here $b(x_i)$ is the bin index where the color component at x_i falls into, and δ is the Kronecker delta function. In our experiment, $8 \times 8 \times 8$ bins histogram is constructed for each region R in RGB color space.

3.2. Weighted histograms

To increase the reliability of the target model, smaller weight are assigned to the pixels that are further away from region center by employing a weighting function

$$g(r) = \begin{cases} 1 - r^2 & r < 1 \\ 0 & \text{otherwise} \end{cases}. \quad (5)$$

Here, r is the distance from the center of the region.

Using this weight, the probability of the quantized histogram in the object model at location \mathbf{y} is given by,

$$p_{\mathbf{y}}^{(u)} = f \sum_{j=1}^I g\left(\frac{\|\mathbf{y} - \mathbf{x}_j\|}{a}\right) \delta[h(\mathbf{x}_j) - u]. \quad (6)$$

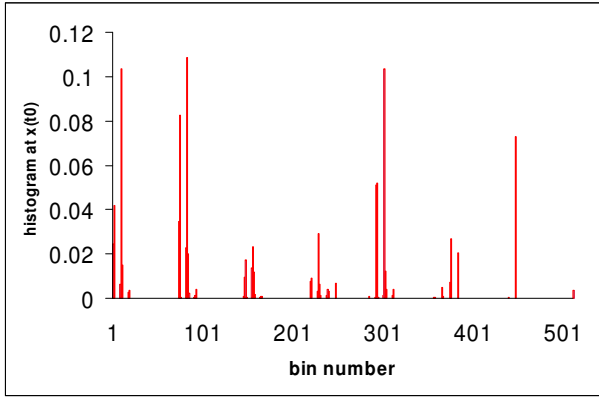
Where I is the number of pixels in the region, \mathbf{x}_j is the position of pixels in the region, δ is the Kronecker delta function, a is the normalization factor, and f is the scaling factor defined as,

$$f = \frac{1}{\sum_{i=1}^I g\left(\frac{\|\mathbf{y} - \mathbf{x}_i\|}{a}\right)}. \quad (7)$$

to ensures that $\sum_{u=1}^m p_{\mathbf{y}}^{(u)} = 1$.

3.3. Distance Measure

A model histogram is the weighted color histogram of the object to be tracked. The model histogram is constructed during the initialization of the system. Fig.1. shows an example of target histogram at time step t_0 . In subsequent frames, at every time t , there are N particles that represent N hypothetical states need to be evaluated. The observation likelihood model is used to assign a weight associated to a specific particle (new observation) depending on how similar the object histogram q and the histogram $p(x_i)$ of the region described by the i^{th} particle x_t^i are.


 (a) histogram of a target at time t_0

 (b) target object at time t_0
Fig.1: Color histogram of a target model during initialization

To evaluate the similarity between the model histogram q and the particle's histogram $p(x_t^i)$, where x_t^i is the i^{th} particle at time t , we employ the Bhattacharyya coefficient ρ ,

$$\rho[p(x_t), q] = \sum_{u=1}^m \sqrt{p_u(x_t)q_u} \quad (8)$$

where u is the histogram bin index. The larger ρ is, the more similar the two distributions are. For two identical normalized histograms we obtain $\rho = 1$, indicating a perfect match. To quantify the distance between two distributions, the distance d is defined as,

$$d = \sqrt{1 - \rho[p, q]} \quad (9)$$

which is known as the Bhattacharyya distance. The observation likelihood function uses this distance to assign a weight to each particle. A sample with small Bhattacharyya distance corresponds to a large weight; similarly, a sample with large Bhattacharyya distance corresponds to a small weight.

The weight $w^{(i)}$ of i^{th} particle of \mathbf{x}_t is calculated as,

$$\begin{aligned} w^{(i)} &= \frac{1}{\sqrt{2\pi\sigma}} \exp\left(-\frac{d^2}{2\sigma^2}\right) \\ &= \frac{1}{\sqrt{2\pi\sigma}} \exp\left(-\frac{(1 - \rho[p(x_t), q])}{2\sigma^2}\right) \end{aligned} \quad (10)$$

3.4. Initialization

The initialization strategy is to put the samples around the region where the target is likely to appear. The tracking mode is begun when the samples satisfy some special appearance conditions. There are many practical applications using initialization strategy. For instance, it can rediscover a tracked target which is occluded by other objects for a long period.

If the target appears, the Bhattacharyya distances of samples around the object position should be remarkable smaller than the average of sample set. Therefore, the mean value μ_b and the standard deviation σ_b of the Bhattacharyya distances of all initial samples are firstly calculated as,

$$\mu_b = \frac{1}{I} \sum_{i=1}^I \sqrt{1 - \rho[p_{x_i}, q]} \quad (11)$$

$$\sigma_b^2 = \frac{1}{I} \sum_{i=1}^I \left(\sqrt{1 - \rho[p_{x_i}, q]} - \mu \right)^2 \quad (12)$$

and then an appearance condition is defined as,

$$d = \sqrt{1 - \rho[p_{x_i}, q]} > \mu + 2\sigma \quad (13)$$

indicating a 95[%] confidence that a sample belongs to the object.

An appearing and disappearing threshold T is defined to indicate the quantity of the samples fulfilling the appearance condition during initialization. More than T means the target being found and starting tracking, contrary situation means the tracker will enter the initialization mode.

An example of initialization strategy is shown in Fig. 2. The samples are initially placed at positions where the object is most likely to appear, like image borders and edge of the occluded object.

4. Particle filter tracking

In this paper, the particle filter tracker consists of an initialization of the target model and a particle filter implementation of a stochastic tracking system. In each iteration, the particle filter tracking algorithm consists of two steps: prediction and update.

The state of the particle filter is defined as $\mathbf{x} = (x, y, \dot{x}, \dot{y}, h_x, h_y, \dot{h}_x, \dot{h}_y)$ where x, y indicate the location of the target, \dot{x}, \dot{y} the motion, h_x, h_y the length of half axes, and \dot{h}_x, \dot{h}_y the scales in the x and y directions, respectively.

In the prediction stage, the samples in the state space are propagated through a dynamic model. In this paper, we use an autoregressive process model which is described by following formulation.

$$\mathbf{x}_t = A\mathbf{x}_{t-1} + \mathbf{v}_{t-1} \quad (14)$$

Here A defines the deterministic component of the model and \mathbf{v}_{t-1} is a multivariate Gaussian random variable, respectively.



Fig.2: An example of initialization strategy

In our application we currently use a first order model for A describing a region moving with constant velocity \dot{x} , \dot{y} and scale change \dot{h}_x , \dot{h}_y .

The update stage applies the observation models to estimate the observation likelihood for each sample. The algorithm of particle filter tracking can be described in following 5 steps and further programming details could refer to [7]:

1. Initialization of the samples:
 - ◆ Given the color histogram of the target model from Eq.6:

$$q = \{q^{(u)}\} \quad (u = 1, \dots, m)$$
 - ◆ Drawing the N particles randomly.
2. Prediction stage : For each particle do the following:
 - ◆ Propagate each sample according to system model of Eq. 14.
 - ◆ Calculate the color histogram $\mathbf{p}_{\mathbf{x}_t}^{\mathbf{u}}$ from Eq. 6.
3. Updated stage : Applying observation model to estimate the observation likelihood
 - ◆ Calculate the Bhattacharya distance from Eq.9.
 - ◆ Calculate the weight from Eq. 10.
4. Estimated position of \mathbf{x}_t according to mean estimate :

$$E(\mathbf{x}_t) = \sum_{i=1}^N w_t^{(i)} \mathbf{x}_t^{(i)}$$

5. Resampling : Generate a new set of samples

$$\{\mathbf{x}_t^{(i)}, w^{(i)}\} \quad (i = 1, \dots, N)$$
 - ◆ Calculate the normalized cumulative probability $c_k^{(i)}$:

$$c_t^{(0)} = 0, \quad c_t^{(i)} = c_t^{(i-1)} + w_t^{(i)}, \quad c_t'^{(i)} = \frac{c_t^{(i)}}{c_t^{(N)}}$$
 - ◆ Generate uniformly distributed number $r \in [0,1]$. Find, by binary search, the smallest j for which $c_t^{(j)} \geq r$ and set $\mathbf{x}_t^{(j)} = \mathbf{x}_t^{(j)}$

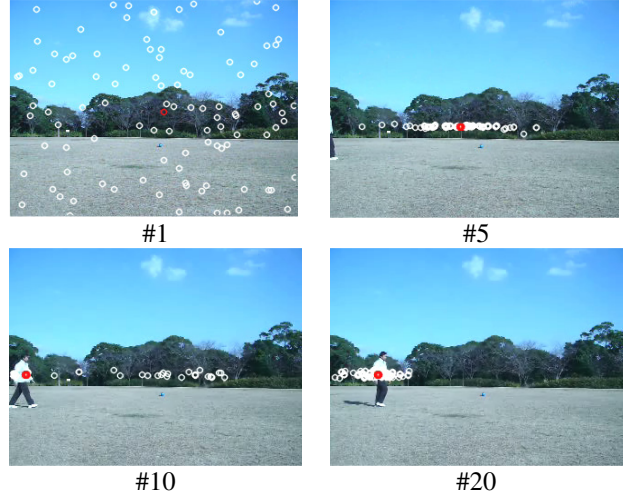


Fig.3: Object tracking with unknown initial position

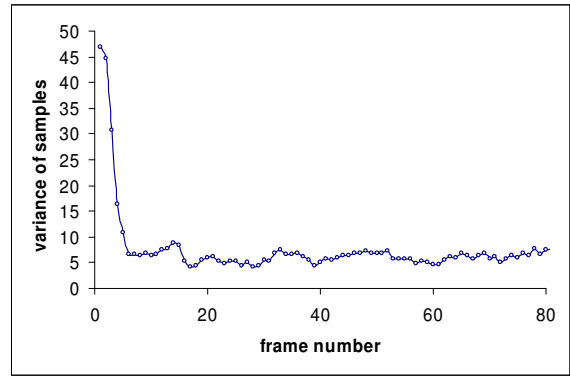


Fig.4: Variance of samples' position

5. Experiments

The algorithm has been implemented and tested using 2.54 [GHz] Pentium IV PC with 512 [MB] memory. The experiment results show that our algorithm works successfully. The size of the input frames is 320×240 pixels. In each experiment, we use 100 particles.

5.1. Object tracking with unknown initial position

In this experiment, we track the moving object with unknown initial position and set to be uniform distribution $x_o \sim U(1,320)$ and $y_o \sim U(1,240)$. The experimental results are shown in Fig.3. The white dots represent the samples' distribution and the red dot represents the mean state of the samples' position. As presented in the figure, initially, the samples are distributed uniformly around the scene. The object moves from left to right and begin to appear in frame #5, however, the object is started to track in frame #10. In this experiment, the variance of the samples' position distribution is utilized to judge whether the object has been tracked or not. As shown in Fig. 4, we consider the object has been tracked when the variance is below 10.

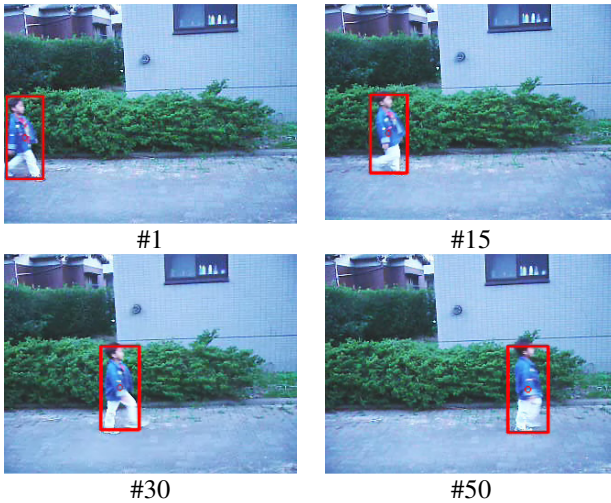


Fig.5: Object tracking with known initial position

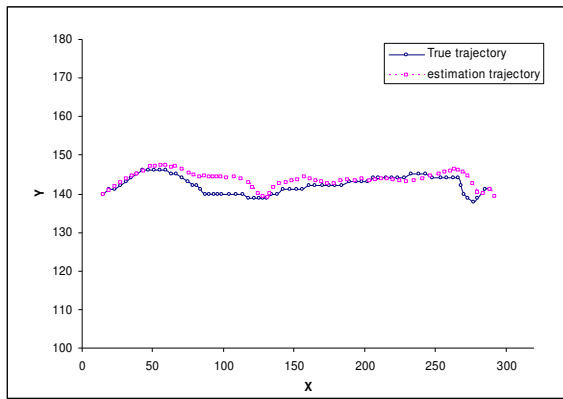


Fig.6: True vs. estimate position

5.2. Object tracking with known initial position

In this experiment, the initial position of the moving object is known and set to $x_o \sim N(22,3)$ and $y_o \sim N(145,3)$. As presented in Fig.5, the object is tracked successfully. The red dot represents the mean state of the samples' position. At the beginning, the samples are distributed around initial position of the object. The object moves from left to right and is tracked from the beginning of frame (frame #1). Fig.6 shows the comparison between true and estimate position of the target object. From that figure, we obtain the RMSE of the estimated position is about 2.06 for X position and 2.18 for Y position.

5.3. Object tracking with appearance condition and occlusion

In this experiment, we apply the initialization strategy to detect and track the object when it is occluded by another object such as tree. The experimental results are shown in Fig.7 and Fig.8. The red dot represents the estimated position of the object and the white dots represent samples' position at each time. As presented in Fig.7, at the beginning, the initial samples positions are placed at the position where the object is most likely to appear, such as image borders and edge of the occluded

object (tree) as shown in frame #1. The object is started to appear at frame #6, but as the appearance condition is not fulfilled, the object is still judged not to be tracked. When the appearance condition is fulfilled (frame #9), the object is judged to be tracked until it is occluded by a tree.

Fig.8 shows the successful object tracking in the presence of occlusion. As shown in that figure, the object is tracked until it disappears behind a tree (frame #45). The final mean state estimate is calculated, but as the appearance condition is not fulfilled, the object is judged to be disappeared (frame #50). Although the object is disappeared, the estimation of the samples set still continues and the dynamic model and the previous state propagations evolve further. The object is tracked again when it appears behind the tree (frame #54), due to the appearance condition and continues to be tracked until the end of the frame.

Number of samples that fulfill the appearance condition is shown in Fig.9. As presented in that figure, the object is detected and started to be tracked when the threshold T is about 10. That means the object is detected and tracked when the number of samples fulfilling the appearance condition is more than 10 samples.

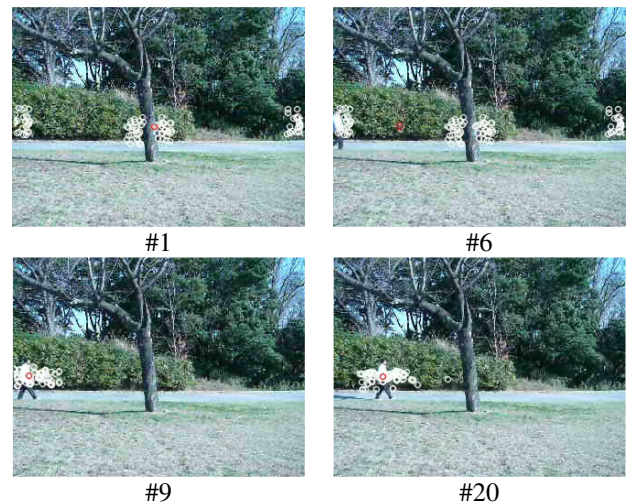


Fig.7: Object tracking with appearance condition

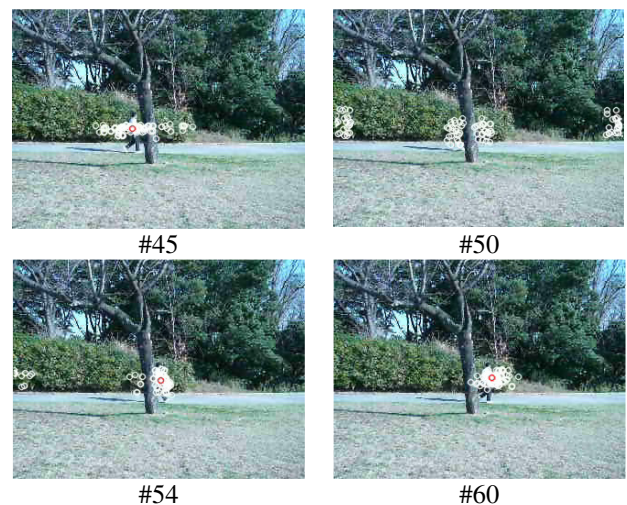


Fig.8: Object tracking with occlusion



From that figure, we can understand that the object is tracked at frame #9 until it is occluded by tree at frame #50. At this time, the number of samples at appearance condition is dropped to zero. At frame #54, the number of samples at appearance condition is 23 and object is begun to be tracked again.

6. Conclusions

In this paper, we presented an efficient and robust color feature-based method for object tracking employing a particle filter algorithm. The utilization of color feature-based histogram as target model makes a particle filter tracking approach more robust. The particle filter maintains multiple hypotheses about the state of the tracked objects by representing the state space by a set of weighted samples. In addition, an initialization strategy is used as tracked target may disappear and reappear. The experimental results illustrate that the method can effectively track the target with both known and unknown initial positions, and also, when the object is occluded by another object using the appearance condition.

Further improvements could be performed to speed up the computational time and to obtain the better result. In addition, performing the proposed method to realize multi-target tracking is also interesting for future researches.

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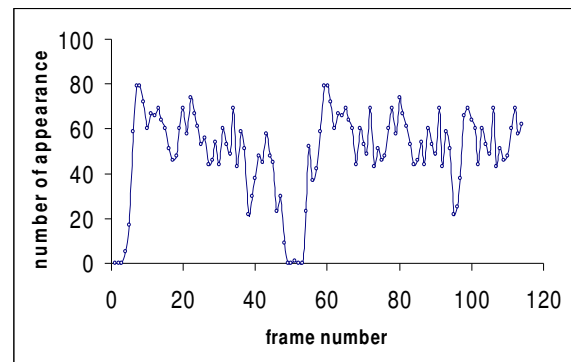


Fig.9: Number of samples fulfilling the appearance condition