SUBPIXEL VISUAL TRACKING BASED ON ADAPTIVE STRATEGIES

Héctor Barrón, Janeth Cruz, Leopoldo Altamirano
National Institute of Astrophysics Optics and Electronics
Luis Enrique Erro No. 1

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Abstract: Several applications based on visual tracking need a better accuracy to perform a more reliable analysis of the objects in scene. However, it is necessary to deal with environments with different atmospheric conditions. Object dynamics can affect tracking throughout time. In this work, a tracking method with subpixel measurements is described, where quality of the state estimate of the object is enhanced. The proposed scheme is robust in scenes with occlusions and changes in appearance of the target. The target model is adapted to size changes of the object, avoiding aperture problem and integration with false information. The state of the object and its aspect along time are estimated. Each pixel is modeled by a random variable because the set of pixels represents the non-observable surface of target where real value of pixels can be affected by noise. This assumption allows the design of a gradual scheme for model updating. Subpixel precision in tracking is based on an iterative method that uses the similitude surface between the target model and the current image of the object on tracking.

1 INTRODUCTION

Object tracking allows to focus computer resources for analysis on objects into dynamic environments. When accuracy in tracking is increased, it is possible to perform an analysis more reliable on study objects in applications where availability of information has a great importance (Awcock, 1996). High accuracy in tracking increases reliability at surveillance systems whose functionality include intelligent motion detection, event analysis and domestic security. However, it is required to deal with dynamic environments where situations with different atmospheric conditions are presented such as rain, haze and dust. Furthermore, it is possible to deal with noise produced by sensor or data transmition, where tracking efficacy is decreased. Another kind of problems are caused by dynamic behavior of the object on tracking.

Image tracking analyzes a projection of the object with respect to the observer. If object come near or far way, object appearance may change. This situation produces that the object model could be not enough to maintain tracking or it could produce incorrect information on the state of tracking object. This paper presents an integral solution for tracking with subpixel accuracy, dealing with size changes on object apparence under dynamic environment.

In section 2, problems and related approaches are described. The proposed method of tracking is detailed in section 3. Finally, results and conclusion are found in sections 4 and 5, respectively.

2 BACKGROUND

A tracking system collects a set of sensor data that contains attributes of objects with potencial interest. This set of data is known as measurements and the object on tracking is known as target. Internally, a target is represented by a state vector whose elements are parameters that characterize its behavior such as position, velocity, size and color. The state is updated by each new measurement. In image-based tracking, it is important for monitoring each spatial and temporal change that an object suffers in a video sequence. So, this process depends on temporal matching, where two images represent the target state at two different instant of time.

2.1 Target detection

Target detection is a process to search an interest object into an image and get its position. This is done

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by image registration, where an image represents the target and another image is the search space. This problem has been studied at different ways, but it is difficult to find a robust and accuracy scheme and it depends of the target representation and the conditions to localize it. Image registration is one of the fundamental tasks in vision systems. However, this is not an easy topic because there are several factors that affect performance of the vision systems as sensor noise, different views of the observer, motion perturbations, changes on objects state by motion and atmospheric and illumination conditions.

Image registration can be defined as mapping between images, considering spatial and intensity differences. Let be I_1 and I_2 images related by

$$I_2(x,y) = g(I_1(f(x,y))) \qquad (1)$$

where f is a spatial transformation between two coordinates and g is a radiometric transformation. Image registration is defined as estimation of geometric and radiometric transformations, such that two images could be compared by detections of coincidences. It is important to realize that if the number of parameters that define the relation between two images of the same object is increased, then the complexity of searching is increased too.

Image registration depends of three elements (Brown, 1992; Zitova, 2003):

- *Characteristic space*. In image registration, it is important to determinate which set of characteristics defines the best representation of image. Selection is affected by different factors and conditions, such as quantity of obtained information, sensitivity to properties of sensor and scene and computational cost. Sometimes, a characteristic space is created with intensity levels at pixels or a transformation on them, as FFT. Another schemes are defined by structural features (borders, contorns, interest points, centroids) or texture properties (contrast, homogeneity, correlation).
- *Similitude measure*. This measure identifies the compatibility degree between two images. Similitude metric is used for finding the required parameters in a mapping between related images. Some of the most used similitude measures are cross-correlation, sum of absolute difference, sum of square difference and phase correlation. Furthermore, it is posible to use methods more complex as bayesian detectors and neural networks. According with application, if characteristics space and similitude metric are correctly selected, then it is possible to ignore some non-relevant distortions for a correct matching.
- *Search strategy*. In case where only displacement is required, it is sufficient with a sequential search to determine mapping. However, if mapping requires more parameters, searching must be more complex. Some techniques used are hierarchy search, relax labeling, dynamic programming and heuristic search. The number of parameters that defines the mapping and computational cost are the most important factors to determine the search strategy.

2.2 Visual Tracking of Objects

Visual tracking is used in a wide range of applications, but there is not an algorithm to be used in whatever conditions. In general, tracking methods can be separed in two groups: tracking based on motion detection and tracking based on models.

Tracking based on motion detection uses detection algorithms as optical flow, gaussian mixture or image difference. This approach has a good performance and it is posible to work on no-rigid objects. However, these schemes do not use a target model, they are sensible to false detections and tend to loss tracking on target, if displacements are very small.

Tracking based on models uses image registration for detection because it is defined a target model. These techniques are more robust and it is possible to use image analysis more complex to obtain measurements. This approach has major computational cost, so deformation of objects must be considered. However, information about behavior could help to enhance efficacy (Hong, 2002).

In (Comaniciu, 2003), an object model is created with a probability distribution function pdf from histogram. The target position is defined by Bhattacharyya coefficient as similitude metric. The search strategy begins on previous position of target and it is guided by a derivative kernel. This approach is fast, an exhaustive search is not required and subpixel measurement is obtained. But, size changes are not supported.

In (Son, 2002), a correlation window is adapted to size changes of targets. Using temporal and spatial gradient between two consecutive images, the occupation ratio in window is obtained. If ratio is less then window is decreased one pixel, otherwise the window is increased. In (Chien, 2000), correlation window is adapted by modeling with motion vectors. Direction and magnitude of contraction or expansion depend on simple image processing. This approach is useful if displacement are small.

Probabilistic approaches have been suitable solutions to above presented problems, such as adaptability in tracking based on target behavior. In (Rasmussen, 2001), it is proposed to take advantage of a set of ramdom samples around prediction of target geometric parameters and to use a pdf as similitude measure. The evaluation of the samples set defines the measurement process, where samples with low probability are eliminated. Remainder samples are integrated to compute real position of the target.

In (Ross, 2004) a method similar to (Rasmussen, 2001) is proposed, where a sampling is performed on geometric parameters of target. This approach includes a gradual updating of target model based on PCA, allowing reliability due false detection.

2.3 Subpixel Measurements

Methods to obtain subpixel measurements can be divided in two groups: techniques based on numeric calculus and techniques based on image interpolation.

The computation of centroid is the simplest method used, and extention is determinated by parabolic or gaussian fitting. This approach produces a set of equations whose result is the point of maximum similitude with subpixel accuracy (Shortis, 1994). These methods have good performance but they have constrain accuracy.

The second approach (Frischholz, 1995) is based on image matching. In general, a sampling is performed on a reference image and each sample image is a possible real position. Later, each image is evaluated to obtain the nearest position with different similitude measures.

Work in (Thevenaz, 1998) presents a method with subpixel accuracy based on interpolation. The search space is formed by a set of parameters of an affine transformation, and the similitude measure is based on squared difference between the reference image and an input image. The measure of similitude is defined by

$$\chi^2(p) = \frac{1}{N}\sum_{i=1}^{N}(f_R(x_i) - f_T(Q_p(xi))^2 \quad (2)$$

where N is the number of pixels, x_i is the coordinate of each pixel, $f_R(x)$ is the reference image, $f_T(x)$ is the input image, Q_p is the geometric transformation defined by vector P. So, the search strategy is an optimization of a no-linear problem that is solved by Marquardt-Levemberg method. In this approach, gradient of the image is used to find the set of parameters that minimize eq. 2. This method converges quickly to an accuracy solution, but it depends on interpolation scheme and a correct initialization of the transformation parameters is required.

3 PROPOSED METHOD

Kalman filter allows to obtain a suitable estimation of the target position, due to its dynamics satisfies with the linear-gaussian assumption. However, when images are used in some application, the discrete nature of pixels causes measurements to get some additive noise no-gaussian, then the estimation is more difficult. When measurements are supplied with subpixel accuracy, filter input has not constrains, hoping to reduce estimation error.

The proposed tracking system allows to get subpixel accuracy and it is reliable due changes of target apparence, in dynamic environments. Taking into account that object localization is non-observable because measurements are affected by noise, then it is required to estimate the target position by means of a random variable. This estimation is provided as prediction to use in real applications.

A general description of the proposed system is given in Fig. 1. An object model is defined to enhance measurements of tracking. At each input image, the target model is searched to get its new position. When position measurement is already obtained, size is measured and subpixel accuracy is calculated. Prediction by Kalman filter allows to know the target position in next image and to define the search space for next measure process.

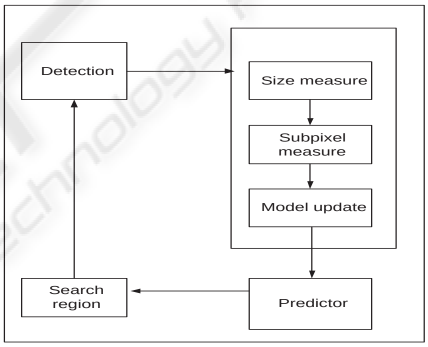


Figure 1: General diagram of the proposed method.

3.1 Representation and Localization

Position measurement of a target into an input image is obtained from a detector based on model. So, it is required to define the target representation, search space and similitude measure.

3.1.1 Target Representation

The target representation is given by two elements: a state vector that describes the target behavior and a model image that represents aspect of target throughout time. First, dynamics of target is resumed by the state vector x_t at time t. Measurement vector is related to state by means of function $z_t = h(x_t)$. Measurements vector is determinated by

$$z_t = [x, y] \quad (3)$$

where x, y is the target position on time t. Second, target surface is presented as a set of pixels in image of the target. However, images could be noised and gray levels at pixels can vary on time. So, the real surface of target may be non-observable then

$$z_I(x,y) = I_R(x,y) + w_i \tag{4}$$

where z_I is the pixel value (x,y), $I_R(x,y)$ is the pixel value that represents the real value of target surface and w_i is gaussian noise. At the target model, value of each pixel is represented by a random variable defined as a gaussian *pdf* I_R, with mean $\bar{I}_R$ and variance σ_{I_R}. This model must be adaptive to changes on aspect of target.

3.1.2 Search Space

In (Rasmussen, 2001), it is suggested that many problems in vision may be solved with a MAP estimator. This measurement process is based on maximization of $p(z_t|I, x_{t-1})$ with measurements z_t, due to an input image and the previous state of target, the most probable measurement is found according to

$$p(z_t|I, x_{t-1}) \propto p(z_t|x_{t-1})p(I|z_t) \tag{5}$$

where $p(z_t|x_{t-1})$ is a *pdf* that describes prediction of the current measurement and $p(I|z_t)$ is a likelihood function that defines probability where a specific image is observable, due position z_t. The likelihood function determines similitude between target model and an input image. The *pdf* $p(z_t|x_{t-1})$ is defined by its mean $\bar{z}_t$ and variance σ_{z_t}, such as

$$p(z_t|x_{t-1}) = N(z_t, \bar{z}_t, \sigma_{z_t}) \tag{6}$$

To determinate if a position (x,y) is located into the set of posible positions, (Stauffer, 1999) defines an approximation for gaussian functions. A gaussian distribution considers a position if this one is located to 2.5 standard deviation around the mean. Approximation is given by M_t, where

$$M_t(x,y) = \begin{cases} 1 & (x,y) \text{ is included} \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

$$\approx p(z_t|x_{t-1}) \tag{8}$$

The search space is defined by a circular area around the position prediction, as it is showed in Fig. 2. This region is set by a gaussian function on the positions space. As the measurements are affected by gaussian noise and real movement of target, detection can be described by a linear dynamic model.

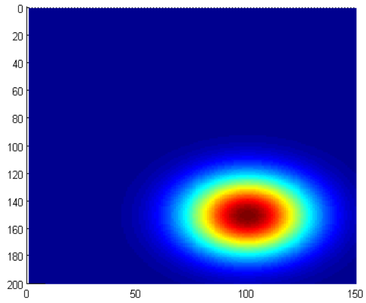


Figure 2: Search space.

3.1.3 Similitude Measure

Target on tracking could have different patterns of intensity, where horizontal and vertical gradients provide information on target aspect. So, the similitude measure must take advantage of all information avaliable on pixels, such as squared difference or normalized correlation. However, it is possible that changes on illumination, low contrast and present noise affect those criterions. Correlation with full sustracted mean (Ronda, 2000) is more robust and allows a larger range of values, and similitude measure is distributed correctly to avoid false detection. A likelihood function based on correlation is defined as

$$p(I|z_t) = sig\left(FSMC(x,y)\right)) \tag{9}$$

with

$$FSMC(x,y) = \left(\sum_{\mathbf{x}} I_R(\mathbf{x})I(\mathbf{x}) - M\bar{I}\bar{I_R}\right) \left(\frac{1}{\left(\sum_{\mathbf{x}} I_R^2(\mathbf{x}) - M\bar{I_R}^2\right)^{\frac{1}{2}}}\right) \left(\frac{1}{\left(\sum_{\mathbf{x}} I^2(\mathbf{x}) - M\bar{I}^2\right)^{\frac{1}{2}}}\right) \tag{10}$$

where sig is the sigmoid function, $\mathbf{x}$ is a position into a image, $I_R(\mathbf{x})$ represents each pixel at image of the target model, $I(\mathbf{x})$ represents each pixel at input image defined as projection of z_t, M is the number of pixels in each the image, $\bar{I}_R$ and $\bar{I}$ are the mean of the target model and the input image, respectively.

3.2 Size Adaptive Tracking

Size and change ratio are parameters that describe dynamics of target. Let be $x_{s,t}$ a state vector that describes the target behavior on scale space. The measurement vector $z_{c,t}$ contains target size related with state vector by

$$z_{s,t} = h(x_{s,t}) \tag{11}$$

The measure process is based on obtaining measurement $z_{s,t}$ that maximize $p(z_{s,t}|I, x_{s,t-1})$. According to Bayes theorem

$$p(z_{s,t}|I, x_{s,t-1}) \propto p(z_{s,t}|x_{s,t-1})p(I|z_{s,t}) \tag{12}$$

where $p(z_{s,t}|x_{s,t-1})$ is a *pdf* that describes prediction on current scale of target and $p(I|z_{s,t})$ is a likelihood function that defines probability of a possible projection of $z_{s,t}$. Further details may be found in (Barron, 2004).

3.3 Precision Subpixel

A pixel-based measure takes advantage of all information on pixels, as interpolation approaches. However, this scheme has a wide search space because it is possible to perform comparations using the full range of real displacements. The method used in this paper is based on search of an optimum geometric transformation using gradients, whose functionality is enhanced by the information intrinsic of a tracking problem.

3.3.1 Similitude measure

The similitude measure is based on difference between image of the target model and an input image, defined by the discrete position of target. The similitude measure is defined as

$$\varepsilon^2 = \int\int_{z \in R^q} (I_R(z) - I_E(Q_p(z)))^2 dz \tag{13}$$

$$= ||I_R(z) - I_E(Q_p(z))||^2 \tag{14}$$

where Q_p is a linear transformation whose parameters are into p,q is the dimension of the coordinate vector z; I_E is a test image and I_R is the target model. Q_p is defined as

$$Q_p(z) = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} \tag{15}$$

where $z = (x, y)$. The transformation that considers displacements of the target is given by

$$Q_p(z) = \begin{bmatrix} 1 & 0 & p_x \\ 0 & 1 & p_y \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} \tag{16}$$

where p_x and p_y are parameters of transformation that represent displacements applied to image and they must be computed in subpixel matching.

3.3.2 Search Strategy

Optimization of the similitude measure defined by eq. 13 is obtained by solving

$$\frac{\partial \varepsilon^2(p)}{\partial p} = 0 \tag{17}$$

using a method no-linear based on gradients, known as *Levemberg-Marquard*. At each iteration of that method, a comparation between I_R and I_E is performed, applying the transformation Q_p. The parameter vector p is updated by

$$p_{t+1} = p_t + \delta p_t \tag{18}$$

with

$$\sum_{i=1}^{M} \alpha_{kl} \delta p_l = \beta_k \tag{19}$$

where α_{kl} is the kl element of a hessian matrix and β_k is proportional to gradient of ε^2. The finite approximation of eq. (13) is given by

$$\varepsilon^2 \cong \chi^2(p) = \frac{1}{N} \sum_{i=1}^{N} (I_R(x) - I_E(Q_p(x)))^2 \tag{20}$$

where N is the pixel number in reference image. To solve the linear-optimization, β_k is computed as

$$\beta_k = \frac{-1}{2} \frac{\partial \chi^2(p)}{\partial p_k} \tag{21}$$

$$= \frac{1}{N} \sum_{i=1}^{N} (I_R(x) - I_E(Q_p(x))) \frac{\partial I_E(Q_p(x))}{\partial p_k} \tag{22}$$

and each element of the hessian matrix is defined as

$$\alpha_{kl} = \frac{1}{2} \frac{\partial^2 \chi^2(p)}{\partial p_k \partial p_l} \tag{23}$$

$$= \sum_{i=1}^{N} \left(\frac{\partial I_E(Q_p(x))}{\partial p_k} \frac{\partial I_E(Q_p(x))}{\partial p_l} \frac{(I_R(x) - I_E(Q_p(x)))}{N} \frac{\partial^2 I_E(Q_p(x))}{\partial p_k \partial p_l} \right) \tag{24}$$

The second derivative terms are usually ignored, so b_{kl} is defined as

$$b_{kl} = \frac{1}{N} \sum_{i=1}^{N} \left[\frac{\partial I_E(Q_p(x))}{\partial p_k} \frac{\partial I_E(Q_p(x))}{\partial p_l} \right] \tag{25}$$

and the set of equation is given by

$$\left\{ \begin{array}{ll} \alpha_{kl} = b_{kl}(1+\lambda) & k = l \\ \alpha_{kl} = b_{kl} & k \neq l \end{array} \right. \tag{26}$$

where $\lambda \geq 0$ defines the updating step for p, given the gradient direction.

3.3.3 Algorithm of Subpixel Matching

In this section, the iterative method is presented to obtain the subpixel measure of the target position.

1. The parameter vector $p = p_0$ is initialized and $\Delta p = 0$ is defined.
2. Image $I_E(Q_p)$ is obtained applying transformation Q_p to the input image.
3. The set of equation is solved to get Δp and p is updated by $p_0 + \Delta p$.
4. RMSE is computed according with the similitude measure.
5. ε^2 is evaluated.
   - If ε^2 is decreased, λ is decreased and $p_0 = p$.
   - Otherwise, λ is increased
6. If current value of ε is equal to above, the process is stopped. Otherwise, it continues with step 2.

It is required to use a reliable scheme of interpolation, such as B-Spline. Indeed, the parameter vector p must be initialized correctly to avoid local minimum, but the above problem is solved with the discrete detection of the proposed system.

3.4 Updating of the Target Model

Such as it is realized in section 3.1.1, each pixel is considered as a gaussian distribution that includes the possible values of the pixel. These values reveal the real surface of the target, considering gradual changes of ilumination or gaussian noise.

So, it is necessary to consider $\{z_I(t)\}$ as the set of values that the pixel has had throughout sequence. The mean and variance that define the gaussian distribution produce a large computational cost. Due to that, an approximation is defined as

$$\bar{I_R} = (1-\alpha)\bar{I_R} + \alpha z_I \tag{27}$$

$$\sigma_{I_R} = (1-\alpha)\sigma_{I_R} + \alpha(z_I - \bar{I_R})^T (z_I - \bar{I_R}) \tag{28}$$

with α as learning ratio. The updating algorithm is performed as follows:

1. After subpixel and size measure, an image used for updating is obtained as a projection of prediction $x_{t|t-1}$.
2. The image is scaled to the model size.
3. A comparation pixel-to-pixel is performed.
   (a) If pixel is located to 2.5 standard deviation, distribution is updated according with eq. (27-28).
   (b) Otherwise, distribution is not affected.

4 EXPERIMENTAL RESULTS

A set of synthetic and real image sequences are used to evaluate the performance of the proposed algorithm and estimate accuracy of the method due to changes in appearance of target, . Three different basis synthetic sequences with 120-180 frames were created, where a target maintains linear or nearly linear movements with displacements between 2-8 pixels. The target size changes from 15×12 to 110×90 pixels and the size change rate is from 1 to 4 pixels per frame. Gaussian noise is applied to each sequence with five different signal-to-noise ratios (SNR) defined as follows:

$$SNR = 20 \log \frac{| \mu_T - \mu_B |}{\sigma_N} \tag{29}$$

where $| \mu_T - \mu_B |$ is the absolute difference of the intensity average between the target and the background and σ_N is the standard deviation of the added Gaussian noise.

It is defined E_p as the error between the correct position of the target and estimated position with the proposed method (eq. 30), X is the value of the coordinate obtained by predictor and X_r is the value of the coordinate in the real position.

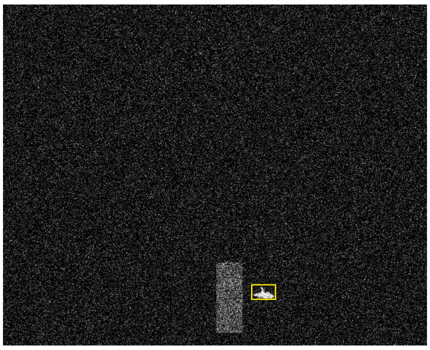
$$E_p = ||X - X_r|| \tag{30}$$

Furthermore, error of size in tracking window with respect to real size of target is defined with eq. 31, where A is the area of estimated window and $\bar{A}$ is the real area of a window to be set around the target.

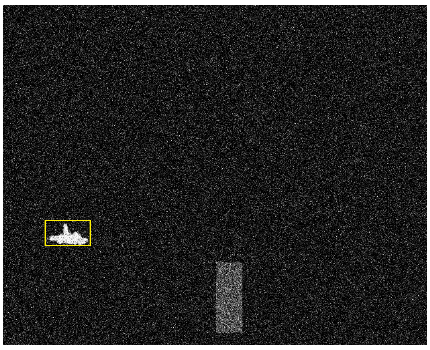
$$E_s = \frac{| A - \bar{A} |}{\bar{A}} \tag{31}$$

In Fig.3, results of the proposed tracking algorithm on a synthetic sequence is shown, where the SNR value is 6dB. In this sequence, the target is affected by size changes and occlusion along of the sequence. The adaptive algorithm maintain the tracking even under occlusion, because it has an estimation of the object appearance when the object appears again.

In Table 1, statistics of displacement error on synthetic sequences are shown with varying SNR from 0.0 to 10 dB. The mean error describes accuracy and standard deviation shows precision of our adaptive algorithm.



(a) Image 79



(b) Image 123

Figure 3: Results in a synthetic sequence.

To evaluate the proposed algorithm in real environments, six different sequences are used. Different objects were selected as target where appearance and size change over time. Targets have linear and nearly linear movements with some atmospheric factors such as snow and haze. In Fig. 4 is shown that adaptive method maintains tracking over sequence Kw, even if target changes of appearance by changing on orientation and size.

The general performance of the adaptive algorithm was of 19-27 frames per second, depending on target size. The subpixel optimization converges with 4-7 iterations throughout time. We demostrated reliability of the proposed method to be compared with two schemes more. A dynamic strategy takes into account changing on the reference image at each frame and a static scheme consists on maintain the reference image without changes along the sequence. To evaluate target position error, we use the absolute difference between real position and the estimated position in this algorithm. Tracking with dynamic strategy over this sequence is affected by the drift problem induced by the discrete nature of the visual tracking. Meanwhile, when the target changes its appearance, the static strategy is obsolete. The adaptive strategy maintains tracking to the end of the sequence.

Table 1: Error in estimation of position.

Error in synthetic sequence				
	Position			
	Pixel		Subpixel	
SNR	Mean	Std. Dev.	Mean	Std. Dev.
10	0.1407	0.1003	0.0451	0.0191
8	0.1601	0.1082	0.0887	0.0674
6	0.2017	0.1607	0.1366	0.0603
4	0.2923	0.1949	0.1545	0.1232
2	0.3057	0.2507	0.1908	0.1345

(a) Image 10

(b) Image 151

Figure 4: Results in real sequence *Kw*.

Fig. 5 shows visual results over sequence Kw. Fig 5(a) shows as the dynamic strategy lost the original object because it actually follows a corner of the target. However, the adaptive strategy maintains the tracking over the original object.

5 CONCLUSIONS

We have presented a visual tracking method based on probabilistic methods where tracking is seen as an image registration problem. Matching between the

(a) Dynamic strategy

(b) Adaptive strategy

Figure 5: Results in real sequence *Nevel*.

reference image and the input image is defined by estimation over the target behavior. Results of experiments over synthetic and real video sequences ensure reliability of the adaptive proposal when the object size changes and occlusions are presented. This work presents comparisons with two techniques to update the reference image where the adaptive probabilistic method gives satisfactory results. The proposed algorithm was tested over sequences in dynamic environments and Gaussian noise. As it was shown, the accuracy was increased in the measurements process, allowing to enhance the estimation of the target in tracking. Another advantage was a scheme to update gradually the target model for improve tracking due to appearance changes. As future work, particle filter could be used to enhance estimation for maneuvering targets and geometric transformation could be extended in optimization method.

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