ARTIFICIAL IMMUNE FILTER FOR VISUAL TRACKING

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Abstract: Visual tracking is an important part of artificial Vision for robotics. It allows robots to move towards a desired position using real world information. In this paper we present a novel particle filtering method for visual tracking, based on a clonal selection and a somatic mutation processes used by the natural immune system, which is excellent at identifying intrusion cells; antigens. This capability is used in this work to track motion of the object in a sequence of images.

1 INTRODUCTION

Artificial intelligence has found a source of ideas borrowed from biological systems such as swarms, ant colonies, neural networks, genetic algorithms and immune systems. They have been successfully used in many different areas: control (Macnab, 2000), optimization (Charbonneau, 2002), pattern recognition (Tashima, 2001), robotics (Ramirez-Serrano, 2004) and prediction (Connor, 1994). The immune system is composed of a complex constellation of cells, organs and tissues, arranged in an elaborate and dynamic communications network and equipped to optimize the response against invasion by pathogenic organisms. The immune system is, in it simplest form, a cascade of detection and adaptation culminating in a system that is remarkably effective, most of the time. It has many facets, a number of which can change to optimize the response to these unwanted intrusions (Dasgupta, 2002). The immune system has a series of dual natures, the most important of which is self - non-self recognition. The others are: general - specific, natural - adaptive, innate - acquired, cell_mediated - humoral, active – passive and primary - secondary. Parts of the immune system are antigen-specific (they recognize and act against particular antigens), systemic (not confined to the initial infection site, but work throughout the body), and have memory (recognize and mount an even stronger attack to the same antigen the next time) (Gilbert, C. , 1994). It can recognize and remember millions of different enemies, and it can produce secretions and cells to match up with and wipe out each one of them. The secret to its success is an elaborate and dynamic communications network (de Castro, 2002). Millions and millions of cells, organized into sets and subsets, gather like clouds of bees swarming around a hive and pass information back and forth. The key to a healthy immune system is its remarkable ability to distinguish between the body's own cells and foreign cells (Bergstrom, 2004). The body's immune defences normally coexist peacefully with cells that carry distinctive "self" marker molecules. But when immune defenders encounter cells or organisms carrying markers that say "foreign," they quickly launch an attack. In this work, we use the intruder detection capability of artificial immune systems in order to track the object in a sequence of images.

2 VISUAL TRACKING

Visual tracking is the action of consistently locating a desired feature in each image of an input sequence. The problem is typically complicated by sensor noise, motion in the scene, motion on the part of the observer and real-time constraints. The problem can be further complicated when more than one identical feature must be tracked, in which case it is up to the observer to decide the optimal set of correspondences which are consistent with a priori assumptions about, and recent observations of, the behavioural characteristics of the features (Prassler, 1990)(Carlsson, 1990). Given an image $I(i,j)i,j \in \aleph^+$, the problem is to track a sub-image (object). In a sequence of images the object will be

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in different positions, moving in a determined pattern. Therefore the prediction part of the filter is needed to predict where the object *I(u,v)* will be in the image *I(i,j)*, giving a region of interest to accelerate the processing of recognizing the object. Recognizing the object by filtering the clutter and noise due to change of illumination, shadows, etc. is the second part of the filter. The use of filters such as the Kalman filter (Gutman, 1990)(Welch, 2001), which is based in optimal prediction for linear system and noise with Gaussian distribution, are excellent tools to overcome the problems in visual tracking. Extensions of the Kalman filter for non-linear systems have been developed such as Extended Kalman filter (Ribeiro, 2004) and Unscented Kalman filter (Jeffrey, 1997). Another algorithm of interest is the condensation (Conditional Density Propagation) (Isard, 1998), which is based on computing the Bayes' rule to a set of particles (particle filtering). In general the filters mentioned above can be seen as Bayesian filters, where the following density distributions are needed (Isard, 1996) (Grewal, 1993):

$p(x_k \mid Z_k)$: A posteriori density given the measurement.

$p(x_k \mid Z_{k-1})$: A priori density.

$p(x_x \mid x_{k-1})$: Process density describing the dynamics.

$p(z_k \mid x_k)$: Observation density

Bayes' Rule is

$$p(x_k \mid Z_k) = \frac{p(z_k \mid x_k)\int p(x_k \mid x_{k-1})\, p(x_{k-1} \mid Z_{k-1})dx_k}{\int p(z_k \mid x_k)\, p(x_k \mid Z_{k-1})dx_k} \qquad (1)$$

One of the drawbacks in these algorithms is the assumption of priori density distribution, Gaussian distribution such in the case of Kalman filter. Particle filters use Bayes (equation 1) and Monte Carlo method to approximate the sequence of probability distribution; these required a large number of particles to converge towards the probability distribution. Therefore, the random sampling is the main drawback, due to in case that the population is not drawn to represent some of its statistical features makes a wrong estimation. Besides, due to the degeneration of the particles through time, re-sampling mechanisms are used. In the next section we introduce an artificial immune system to filter noisy signals and predict the state of a system.

3 ARTIFICIAL IMMUNE FILTER (AIF): CLONAL SELECTION AND SOMATIC MUTATION

The clonal selection theory, by immunologist Frank Macfarlane Burnet (Burnet, 1978), models the principles of an immune system. When an antigen is present in our body, the **B**-Lymphocyte cells produce antibodies **Ab** receptors. Each **B** cell has a specific antibody as a cell surface receptor. The arrangement and generation of antibody genes occurs prior to any exposure to antigen. When a soluble antigen is present, it binds to the antibody on the surface of **B** cells that have the correct specificity. These **B** cell clones develop into antibody-producing plasma cells or memory cells. Only **B** cells, which are antigen-specific, are capable of secreting antibodies. Memory cells remain in greater numbers than the initial **B** cells, allowing the body to quickly respond to a second exposure of that antigen, as show in Figure 1 (de Castro, 2002).

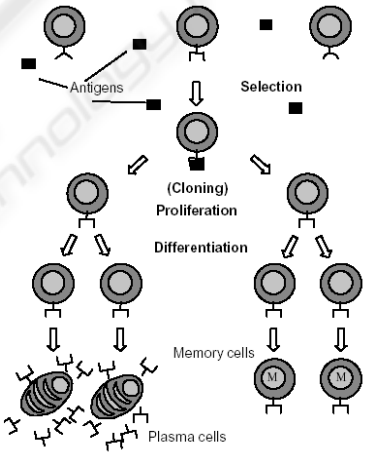

Figure 1: Clonal Selection Principle.

The higher affinity comes from a mechanism that alters the variable regions of the memory cells by specific somatic mutation. This is a random process that by chance can improve antigen binding. This same principle is the inspiration in this work to produce an artificial immune filter. Initial set of *n* **B**-cells (particles) $X = (x^1, x^1, ..., x^n)$, representing the features of our object to track (positions, velocity, etc), weights $W = (w^1, w^2, ..., w^n)$, representing its affinity between the antigens and the antibodies, and memory cells $S = (s^1, s^2, ..., s^m)$, are created. In the beginning our best affine cell to our antigen is our

initial condition. Therefore we clone and slightly mutate the cell, using equation (2)

$$x_k^i = x_k^{best} + \alpha r_k^i \tag{2}$$

where r is a random variable normally distributed $r \sim N(0,1)$ and $\alpha \in \Re$ is a small constant. The affinity w_i is integrated by two distance measurements from our best B cell, before and after prediction. Equation (3) is the first part of affinity

$$af_1^i = \exp\left(-\left\|x_k^{best} - x_k^i\right\|\right) \tag{3}$$

The next step *k+1* is the prediction part, given by $x_{k+1}^i = f(x_k^i)$ for nonlinear dynamics and by $x_{k+1}^i = Ax_k^i$ for linear dynamics, where A is known as the transition matrix. After all the cells have been through the dynamic system, it is time to obtain a new measurement z_k, which contains a certain level of noise. Then we apply equation (4) to obtain the second part of our affinity measurement, where H is the observation model in the case of a linear system and β is a constant.

$$af_2^i = \exp\left(-\beta\left\|z_k - Hx_{k+1}^i\right\|\right) \tag{4}$$

$$w_i = af_1^i + af_2^i \tag{5}$$

Equation (5) calculates the affinity of each **B**-cell to the antigen. The m best cells with high affinity will conform to our memory cells, and the highest affinity will be the estimation $\bar{x}_{k+1}$ and our next best **B**-cell x_{k+1}^{best}.

3.1 Application of Artificial Immune Filter to Noise Rejection

Before applying the artificial immune system to visual tracking, the filter was tested on a noisy signal and compared to a Kalman filter. The signal represents the antigen to be recognized. The best **B**-cell that binds the antigen is the estimation of the state of the signal. The next stage is choosing the parameter for mutation, α. Since the level of somatic mutation for the cells is a slight change on our best **B**-cell, a value equal or less than *dt* value, the step time of the system, is a good option, because it indicates that **B**-cells could vary $\pm dt$ (0.01 for this example) from their real values.

Given a linear stochastic difference equation in the next form

$$x_{k+1} = Ax_k + bu_k + w_k \tag{6}$$

$$z_k = Hx_k + v_k \tag{7}$$

where

$$A = \begin{bmatrix} 1 & dt \\ -dt & 1 \end{bmatrix} \quad b = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \quad H = \begin{bmatrix} 1 & 0 \end{bmatrix} \quad u_k = 0$$

Noise is modelled by

$$w_k = \begin{bmatrix} 0.15 \cdot dt^2 \cdot r_k \\ 0.15 \cdot dt \cdot r_k \end{bmatrix} \tag{8}$$

$$v_k = \left[0.1 + 0.05\sinh(r_k)\right] \tag{9}$$

Equation (9) introduce a heavily spike noise with non zero mean, while equation (8) is a normal distribution, and r is random noise. Figure 2 shows the measured position with noise up to 50% of its maximum value.

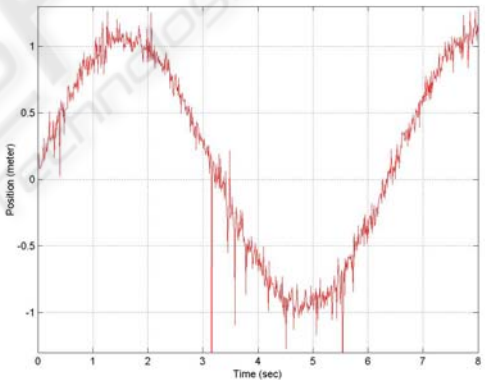

Figure 2: Measured position.

Using the proposed algorithm of Figure 3, we obtained the filtered signal in Figure 4.

x_{best}=*Xinitial_condition*
$S = \{\phi\}$

1. Clonal Selection of B-cells and Somatic Mutation
For $i=1$ to n
$x_i = x_{best} + \alpha$
if $S \neq \{\phi\}$
Replace $x_{n-m} = S(1..m)$
$x_i = x_i + \alpha\ r$
endif
$af_1 = dist(x_{best}, x_i)$
endfor

2. Prediction and affinity with measurement
$x_{k+1} = f(x_k)$
$af_2 = dist(Z, X_{k+1})$

3. Total affinity and Selection of m Memory Cells
$W = af1 + af2$
$S = Sort(W)$ **from bigger to small**
Choose list of m cells $S(1..m)$
$X_{best} = S(1)$

4. Go to step 1

Figure 3: Pseudo-code for Artificial Immune Filter.

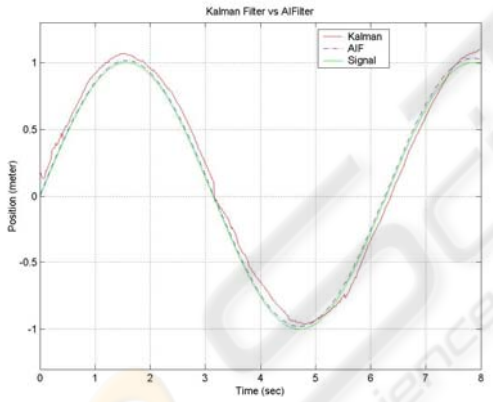

Figure 4: Performance of Filters.

It is well known that the uncertainty of the covariance parameters of the process noise, *Q*, and the observation errors, *R*, has a significant impact on Kalman filtering performance. *Q* and *R* influence the weight that the filter applies between the existing process information and the latest measurements. Errors in any of them may result in the filter being suboptimal or even cause it to diverge. The conventional way of determining *Q* and *R* requires good a priori knowledge of the process noises and measurement errors, which normally comes from intensive empirical analysis. Besides of the errors due to covariance parameters, the Kalman filter is based on the assumption of normal distribution noise with zero mean. Figure 4 shows the real signal with no noise and the filtered signal. It can be seen that the filter affectively attenuated the noise. In this example we use the following parameter settings for the Kalman filter,

$$Q = \begin{bmatrix} 0.00015 & 0.015 \\ 0.015 & 0.00015 \end{bmatrix} \qquad R = 0.0025 \qquad P = Q$$

The parameter settings for the AIF were, *n=20*, *m=5*, $\alpha = [0.001 \quad 0.01 \quad 0.01]$, $\beta = 0.1$.

3.2 Visual Tracking using AIF

Tracking an object in a sequence of images is a challenging problem. An elementary tracking approach could be to fit a curve, (contour of an object) to each image in a sequence, and an estimated curve is therefore required for each image. Then a fitted curve from one image is the estimation for the next image. This kind of algorithm will be affected by fast motion and become sensitive to distractions. Clutter in the background, either static or dynamic, noise of the sensor and change of illumination, are some factors to consider as noise in an image (Healey, 1994). The tracking performance can be greatly improved by a filter able to predict and correct the fitted curve, removing the noise from the image. Our artificial immune filter is used in this section to track an object in a sequence of images. The extension of the artificial immune filter from single variable to multivariable is straightforward. The contour of the object is a parametric curve

$$c(t) = (Ix(t), Iy(t)) \qquad t \in [0, L] \qquad (10)$$

where t is an independent parameter over the interval *[0,L]*, and *Ix(t)* and *Iy(t)* are known as spline functions (Foley, 1990). An important aspect to achieve real time tracking performance has been the restriction of measurements of the set of observations *Z* to a sparse set of lines normal to the contour of the object, as shown in Figure 5. In this case the affinity is given by

$$af_2^i = \sum_{j=1}^{P} \exp\left(-\left\| z_k^j - C_k^i(t) \right\|\right) \qquad (11)$$

where *P* is the number of searching lines and z_k^j is the edge closest to the hypothetical contour $C_k^i(t)$.

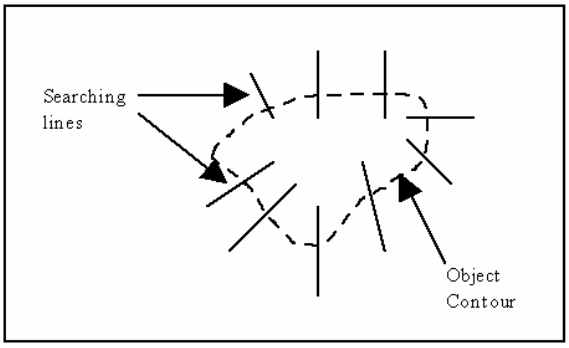

Figure 5: Normal lines of object contour to search the observation z_i.

Figure 6 shows a sequence for fast tracking motion of a ball with clutter added to background. This experiment used 100 cells and 10 memory cells, in real time (30 frames per second). In spite of the fast motion of the ball, the tracker never loses contact with the ball in a sequence of image, when we bounced the ball several times against the wall. The tracker shows the center of the ball with white dots.

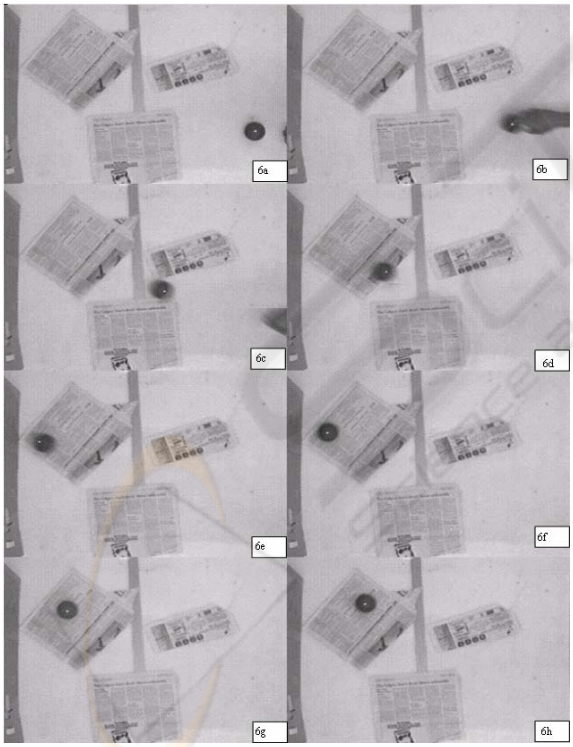

Figure 6: Tracking a fast motion ball.

Figure 7 is a group of snapshots from a tracking sequence of the ball under heavy clutter, dynamic background and partial occlusion.

Figure 7: Tracking using Artificial Immune Filter.

4 CONCLUSIONS

In this work we introduced a novel filter using a clonal selection and somatic mutation model of immune system. The filter does not require probability distributions or re-sampling, unlike other particle filters. The artificial immune filter was tested for signal processing and visual tracking, showing good performance in both applications. In the application of visual tracking of the ball, the filter was able to track fast ball motion in a non-smooth trajectory (bouncing) and clutter in the background. Future work will include the adaptation of parameters and tracking of several objects.

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