## IIT Model: Parameter Optimization

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The simulational experiment is carried out using road, noise or blank background with an object moving either vertical or horizontal in constant speed.

### 1 Field of View(degree)

Field of view $\theta$  is defined as the wideness of the camera angle.  $\theta$  decides the number of pixels per degrees in 1 degree sampling thus defines the size of grid image, or eye size, been processed in photo receptor using the following equation:

$$Pixel/degree = \frac{Size_{image}}{\theta} \tag{1}$$

A small  $\theta$ (low definition) reduce the accuracy of target location detection while a large  $\theta$  limits the built-up of facilitation. Fig(1) illustrates the affect of  $\theta$ .

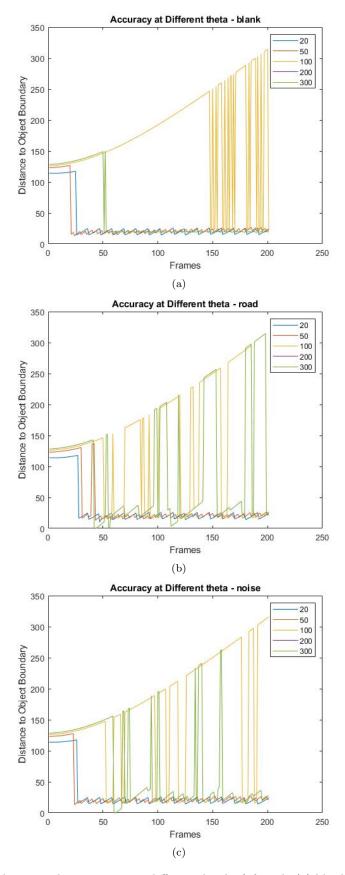


Figure 1: Tracking horizontal movement at different level of  $\theta$  with (a).blank background (b).road background and (c).noise background

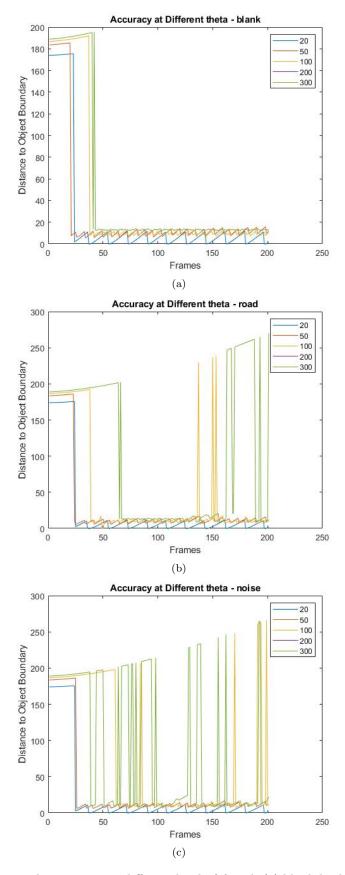


Figure 2: Tracking vertical movement at different level of  $\theta$  with (a).blank background (b).road background and (c).noise background

#### 2 $\omega$ Parameter

 $\omega$  varies the time constant of the facilitation low-pass filter, thus controlling the duration of enhancement. The filter here is an single pole IIR(infinite impulse response) filter that processes as follow:

$$y_n = \beta x_n + \alpha y_{n-1} \tag{2}$$

where:

$$\alpha = (1, \frac{Ts \times \omega - 2}{Ts \times \omega + 2}) \tag{3}$$

and:

$$\beta = (Ts \times \omega + 2, Ts \times \omega + 2) \tag{4}$$

Ts is the sampling time and is originally assigned to 0.05. When  $\omega$  is low,  $\beta$  vector close to 0, making the facilitation matrix close to 0 thus no tracking can be performed in some condition; when  $\omega$  is too high the entire visual area saturates quickly, reducing the weight of RTC output and lead to a poor target tracking performance. As shown in Fig(3) and (4), the suitable  $\omega$  dependent on complexity of the background and the speed of the moving object: a fast moving object requires larger value of  $\omega$ .

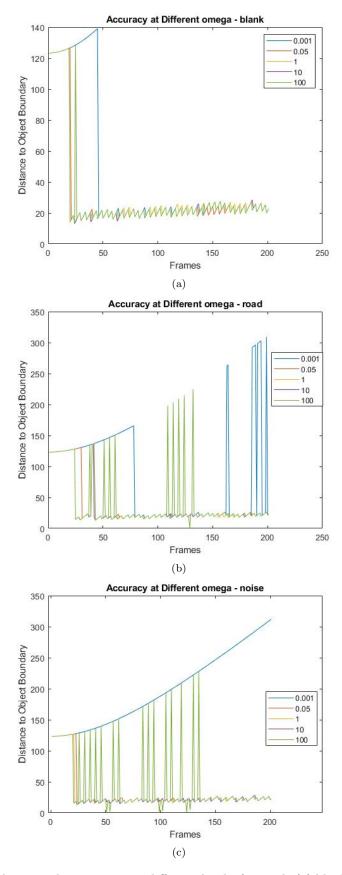


Figure 3: Tracking horizontal movement at different level of  $\omega$  with (a).blank background (b).road background and (c).noise background

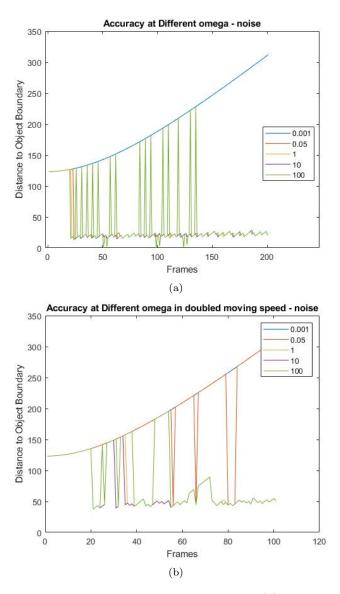


Figure 4: Tracking vertical movement at different level of  $\omega$  with (a).original speed (b).doubled speed with noise background

# 3 Kernel for Weak CSA(Centered-surrounded Antagonism) in LMC

The LMC(large monopolar cells) unit uses temporal band pass filter and CSA to remove redundant information in visual field. The temporal filter model mimics the neural impulse of LMC, thus the parameters are somehow idealised and will not be considered here(however in future we could try other filter model to see if they gives better result). The kernel in other hand accentuate the edges by given negative weight of every pixels surrounding. The ideal kernel size depends on the size of the object. 2 different size of kernel:

$$K_{1} = \begin{bmatrix} -1/9 & -1/9 & -1/9 \\ -1/9 & 8/9 & -1/9 \\ -1/9 & -1/9 & -1/9 \end{bmatrix} K_{2} = \begin{bmatrix} -2/25 & -2/25 & -2/25 & -2/25 \\ -2/25 & -1/25 & -1/25 & -1/25 & -2/25 \\ -2/25 & -1/25 & 40/25 & -1/25 & -2/25 \\ -2/25 & -1/25 & -1/25 & -1/25 & -2/25 \\ -2/25 & -1/25 & -1/25 & -1/25 & -2/25 \\ -2/25 & -2/25 & -2/25 & -2/25 & -2/25 \end{bmatrix}$$
(5)

are tested with target radius 1, 8 and 13:

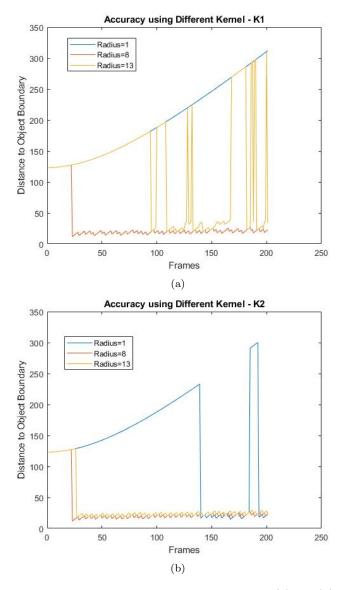


Figure 5: Tracking horizontal movement using (a).  $K_1$  (b).  $K_2$ 

A larger size of kernel increases the range of detectable object size. For small size kernel this range can also been increased using stronger antagonism. Fig(6) shows the result after doubled the value in  $K_1$ 

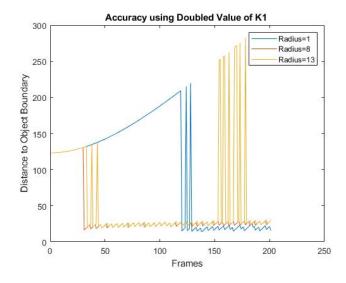


Figure 6: Tracking horizontal movement using  $K_1 \times 2$ 

## 4~ Kernel for Weak CSA (Centered-surrounded Antagonism) in RTC

RTC(Rectifying transient cell) performs adaptation to increase and decrease of light. Varying the gain and spatial extent of CSA in RTC would adapt to target with different size.

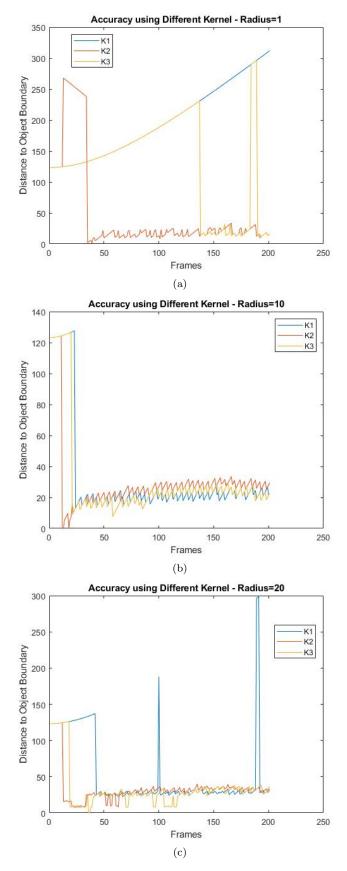


Figure 7: Tracking horizontal movement using (a). $K_1$  (b). $K_2$