An Insect Inspired Object Tracking Mechanism for Autonomous Vehicles

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1 PROJECT SUMMARY

Target tracking is a complicated task from an engineering perspective, especially where targets are seen against complex natural scenery. Due to the high demand for robust target tracking algorithms much research has focused in this area. However most engineering solutions developed for this purpose are either unreliable in real world conditions or too computationally expensive to be used in many real-time applications. Insects, such as the dragonfly, solve this task when chasing tiny prey, despite their low spatial resolution eye and small brain suggesting that nature has evolved an efficient solution for target detection and tracking problem.

This project aims to develop a robust, closed-loop model inspired by the physiology of insect neurons that solves this problem, and to integrate this into an autonomous robot. This system is tested in software simulations using MATLAB/Simulink. In near future this system will be integrated with a robotic platform to examine its performance in real world environments to demonstrate the usefulness of this approach for applications such as wildlife monitoring.

2 STAGE OF THE RESEARCH

This project is started in April 2013 as PhD project and it is at intermediate stage. The computational model inspired by physiology of insects has been tested and optimized using MATLAB/Simulink. The results of simulations show that the model can robustly detect and pursue targets of varying contrast against complex natural backgrounds. The current stage of this project is implementing this model in a hardware platform and testing its ability in real world conditions.

3 OUTLINE OF OBJECTIVES

The aim of this project is to develop a robust, efficient, and cost effective closed loop algorithm to track and chase targets for autonomous terrain robots. This prototype will be designed to track small objects based on the recent findings from flying insect behavior and electrophysiological recordings of their neural system. The objectives of this project can be categorized as two primary goals:

1- To develop a robust closed loop algorithm to track and chase targets even against cluttered background and in the presence of other distracters.

2- To implement the model on a hardware platform to provide a base for applications such as surveillance and wildlife monitoring.

4 RESEARCH PROBLEM

Detecting and tracking a small moving object against a cluttered background is one of the most challenging tasks for both natural and artificial visual systems. Due to the increasing demand for automation, developing a robust tracking algorithm has been the focus of much research during the last decade (Cannons, 2008). The potential applications for such visual target tracking systems include autonomous vehicle navigation, map building, surveillance systems, wildlife study, human assistance mobile robots, and bionic vision. All these applications and many others identify a common requirement for technology that can successfully extract features of interest, track them robustly within complex environments through long trajectories and do so even in the presence of other distractions.

Many algorithms have been developed over the last decade to address the problem of object

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detection and tracking for different scenarios. Most of these methods use assumptions to simplify the situations and make the tracking problem tractable. For instance, smoothness of motion, minimal amount of occlusion, illumination constancy, high contrast with respect to background, etc., are the common simplifications in most of the developed algorithms (Yilmaz et al., 2006). Consequently, most of these methods collapse when it comes to tracking objects in real world situations, within a distracting environment or in the absence of relative background motion. Moreover, most of these methods and techniques involve complex and time consuming computational mechanisms which require huge processing capacity that makes them impractical in many applications. This identifies a clear need for an alternative and more efficient approach to solving at least a subset of the target tracking problem.

While engineering methods try to solve the problem of target detection and tracking by using high resolution cameras, fast processors, and computationally expensive methods, studies of insect visual systems and flying behavior suggest there is a simpler solution. Insects are an ideal group to draw inspiration from in this context since they have a low spatial acuity visual system, angular resolution of approximately 1° (Stavenga, 2003), and a small size, light-weight and low-power neuronal architecture. Nonetheless, they show remarkable visual guided behavior in chasing other insects, e.g. for predation, territorial or mating behavior, even against complex moving backgrounds (Collett and Land, 1975, Wehrhahn, 1979) or in the presence of distracting stimuli (Corbet, 1999, Wiederman and O'Caroll, 2013). These features have motivated extensive research to investigate the neural system that underlies processing for such a complex task. Electrophysiological recordings have been used to examine sensitive cells to small moving objects in different species such as blowfly (Wachenfeld, 1994), dragonfly (O'Carroll, 1993), fleshfly (Gilbert and Strausfeld, 1991), and hoverfly (Collett and Land, 1975).

Moreover, flying insects uncouple the eye from their bodies to actively control their gaze direction and stabilize the image during flight. This active gaze control may simplify and improve tracking strategies for many real-world applications, yet it is a strategy little used in existing artificial vision systems that face many of the same problems of limited spatial and temporal resolution as insects.

Figure 1: Insects must have evolved a relatively simple and efficient solution to a task that challenges the most sophisticated robotic vision systems - the detection, selection and pursuit of moving features in cluttered environments.

Fortunately, as a result of the recent breakthroughs in understanding biological vision we are now at a point where modeling and implementing similar strategies in an autonomous system is a practical possibility. This project therefore aims to adopt a bio-inspired approach to target tracking and pursuit, based largely on recent research on the insect visual system, and will implement it on a ground robotic platform, complete with an active gaze control system.

5 STATE OF THE ART

Traditionally, computer vision techniques divide the problem of target tracking into two subproblems: detection of moving objects and tracking of moving objects (Ren et al. 2003). Dependent on the method, object detection might be required in every frame or when the object first appears in the video (Yilmaz et al., 2006). The object tracker locates the position of the target in every frame of the video and generates its trajectory (Yilmaz et al., 2006). In recent years, some research has shown that the integration of image-based target detection and tracking improves the robustness of the overall system (Wang et al. 2008, Kalal et al. 2012).

5.1 Detection of Moving Objects

In the literature, three typical approaches are used in object motion detection: optical flow, temporal difference and background subtraction:

5.1.1 Optical Flow

Optical Flow methods involve calculation of estimates for local motions in an image, and the determination of the relocation of each pixel in sequential image frames. Most optical flow methods use spatial and temporal partial derivatives to determine the velocity of each pixel in successive images. This method is capable of detecting moving objects even in the presence of camera motion and background changes, though these changes should be relatively small due to a 'smoothness constraint' (Lu et al., 2008). One common assumption in developing optic flow algorithms which limits its applicability in real world scenarios is illumination uniformity (Zelek, 2002). Furthermore, the computational complexity of these methods makes them less suitable for implementation in real-time applications.

5.1.2 Temporal Difference

These methods find contours of moving objects via the difference of two successive frames in a multi-frame image, assuming illumination is constant and the background is stationary. This method applies a threshold on the absolute time difference of two adjacent frames to identify moving objects. The temporal difference method can effectively accommodate environmental changes, but it is usually unable to completely represent shapes of moving objects. The main advantage of this method is its simplicity and low computational complexity, however, it is very sensitive to threshold. A small threshold causes noisy outcomes, while a large one leads to losing essential information of the objects (Yi and Liangzhong, 2010). Moreover, in temporal difference methods a very fast moving object might be detected as two distinct objects (Yi and Liangzhong, 2010).

5.1.3 Background Subtraction

This method is the most popular and developed method for moving objects detection. This method uses a reference frame as a "background image" and this reference frame is kept updated to represent the effect of varying luminance and geometry settings (Piccardi 2004). Therefore, the moving objects are detected by finding the deviation of the current frame from the background image.

Background subtraction provides high quality motion information and has less computational complexity than optical flow. Nevertheless, like the temporal difference method, it requires a stationary background scene with respect to the viewpoint and it is sensitive to scene changes caused by light, weather etc.

5.2 Tracking of Moving Objects

Methods for tracking of moving objects can be categorized as (i) discrete feature trackers, (ii) contour trackers, and (iii) region-based trackers:

5.2.1 Discrete Feature Trackers

Discrete feature trackers use image features such as discrete points, edges and lines to track an object. Point trackers match the object frame-to-frame based on the previous object position and motion. Both edge trackers and 3D model trackers focus on line elements of the object as many man-made objects are composed of numerous straight lines. The difference between these two classes is whether or not the tracker uses a three dimensional object model.

Many successful tracking methods have been developed based on point trackers (Veenman et al., 2001, Sahfique and Shah, 2003). The work of Sahfique and Shah (2003) shows a high level of accuracy despite a significant level of noise in the scene. Although some proposed point tracking methods can cope with occlusions and foreground clutter, these methods have not effectively addressed the effect of illumination changes (Cannons, 2008).

The other groups of discrete feature tracking, edge (Zhang and Faugeras, 1992, Jonk et al., 2001, Mörwald et al., 2009) and 3D model trackers (Leng and Wang, 2004, Lepetit et al., 2005), are less developed compared with point trackers. These groups of trackers are mostly robust to illumination since spatiotemporal filtering is applied on their front end, and they are capable of handling some extent of occlusion. Unlike the edge trackers, 3D model based ones can deal with scale changes. However, both of these methods have mostly been examined only under simple and controlled environments. Hence, their performance under real world conditions and cluttered environments is, as yet, largely unknown (Cannons, 2008).

5.2.2 Contour Trackers

A contour tracker is defined as any system that follows a target from frame-to-frame and represents the target with an open or closed curve that adheres to its outline. Although both contour trackers and line trackers track the boundaries of targets within the scene, line trackers are limited to following straight line segments. Therefore, since boundary representation of the contour trackers are drastically different from a straight line (e.g., a circle), the techniques used for these two types of trackers are quite different.

Contour trackers have been significantly improved since their original inception. Different contour trackers have been proposed (Paragios and Deriche, 2000, Li et al., 2006, Mansouri, 2002, Yilmaz et al., 2004, Bibby and Reid, 2008, Bibby and Reid, 2010) to address some of the issues related to object tracking, such as automatic initialization and occlusion. Although these approaches have successfully solved some issues, none are truly robust to background clutter.

5.2.3 Region-based Trackers

A region-based tracker is a type of tracker which represents the target by maintaining feature information across an area. The types of features that are used in region trackers include color, texture, gradient, spatiotemporal energies, filter responses, and even combinations of the above modalities.

Research based on region trackers shows very robust results in terms of occlusion (Comaniciu et al., 2000, Cannons and Wildes, 2007). This class of trackers can handle background clutter more robustly than other classes as long as the clutter in the background is stationary and occlusion is not significant (Comaniciu et al., 2000, Birchfield and Rangarajan, 2005, Cannons and Wildes, 2007, Yin and Collins, 2007). Nonetheless, these types of trackers are very sensitive to changes in illumination.

5.3 Estimation Tools

In some tracking research, algorithms tools such as Kalman filter, Extended Kalman filter, Unscented Kalman filter, and particle filter have been employed to enhance the accuracy of target tracking (Boykov and Huttenlocher, 2000, Li and Chellappa, 2000, Rui and Chen, 2001, Li et al. 2003).

5.3.1 Kalman Filter and its Variations

The Kalman filter is a prediction and correction tool which uses the states of the previous time step and observable measurements to compute a statistically optimal estimate for the hidden states of a system. Although a Kalman filter can provide a powerful estimation tool, it has limitations. The mathematical model of the Kalman filter assumes that the dynamic model is linear but some systems are not well-described by linear equations. Another limitation of the Kalman filter arises from modeling the measurement uncertainties by white Gaussian noise processes. There are many instances where this simplified model is not appropriate such as tracking a target throughout a cluttered environment, where the measurement distribution might not be a unimodal Gaussian.

The 'Extended Kalman Filter' (EKF) is a variation of the Kalman filter developed to provide prediction and correction for non-linear models. In the extended Kalman filter framework, Taylor series expansion is used as a linear approximation of non-linear models. The strength of the EKF lies in its simplicity and computational efficiency. Nonetheless, unlike the Kalman filter, the extended Kalman filter in general is not an optimal estimator. In addition, due to the extended Kalman filter’s sensitivity to linearization errors and covariance calculations, the filter may quickly diverge.

The 'Unscented Kalman Filter' (UKF) is another popular non-linear variation of the Kalman filter. The UKF utilizes deterministic sampling methods to represent the measurement and state variables. The UKF tends to be more robust and more accurate than the EKF in its estimation of error. However, neither the EKF nor the UKF solve the cases where white Gaussian noise cannot be used as estimation descriptor of measurement uncertainties.

5.3.2 Particle Filter

A particle filter or sequential Monte Carlo filter maintains a probability distribution over the state of the object being tracked by using a set of weighted samples, or particles. Each 'particle' represents a possible instantiation of the state of the object. In other words, each particle is a guess representing one possible location of the object being tracked and the denser the portion of particles is at one location, the more likely the target is there.

The main advantage of a particle filters over a Kalman filter and its variations is its applicability to nonlinear models and non-Gaussian noise processes. Although with sufficient number of samples particle filters are more accurate than either the EKF or UKF, when the simulated sample is not sufficiently large, they might suffer from sample impoverishment.

The addition of these filters to tracking algorithms decreases the noise in the image and produces a more accurate estimation of the position of a target within the scene. Although the robustness of described tracking algorithms (Section 5.2) increases in conjunction with these filters, the computational complexity associated with these algorithms still remains an unsolved issue.

5.3.3 Physiological Approaches

As an alternative to the traditional engineering approaches, there has been recent research which has used biologically inspired approaches for detection and tracking. Wiederman et al. (2008) developed a size selective, velocity tuned, contrast sensitive bio-mimetic model based on electrophysiological experiments (Figure 2) from ‘small target motion detector’ (STMD) neurons, in response to the presentation of various visual stimuli. This 'elementary small target motion detector' model (ESTMD) emulates the different stages of visual processing in flying insects consisting: (i) fly optics, (ii) photoreceptors, (iii) large monopolar cells and (iv) rectifying transient cells.

(i) Optics of the insect compound eye consisted of thousands of arranged facet lenses which their diffraction limit the spatial resolution of the eye to approximately 1°.

(ii) Photoreceptors in the retina dynamically adapt to background luminance (Laughlin, 1994), reduce noise and improve the SNR by altering their contrast gain (Juusola et al., 1994).

(iii) Large Monopolar Cells (LMCs) in the insects' lamina remove redundant information (Coombe et al., 1989) by acting as a spatiotemporal contrast detector (Wiederman et al., 2008).

(iv) Rectifying Transient Cells (RTC) of the medulla have independent adaptation of ON and OFF channels (reverse polarities).

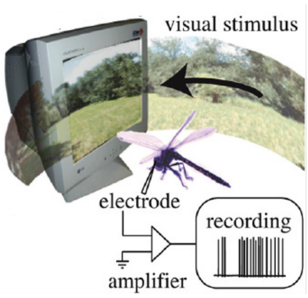

Figure 2: Electrophysiological recordings from STMD neurons. The visual stimuli are displayed, whilst the electrical potential (spikes) from inside the brain cell is being recorded.

Recent studies on dragonflies reveal that one type of STMD neuron, CSTMD1, has a facilitatory role in tracking targets. The spiking activity of CSTMD1 builds over time in response to targets that move through long, continuous trajectories (Nordström et al., 2011). Dunbier et al. (2011, 2012) recorded the response of these neurons to stimuli traversing in interrupted paths. These electrophysiological recordings show that these neurons responses reset to a naive state when there are large breaks (~7°) in the trajectory path. This facilitatory mechanism can enhance the response to weak stimuli. Moreover, this mechanism directs the attention to the estimated reappearance location of the object which increases the robustness of pursuit even if the target is temporarily invisible. The same analogy can be found in probabilistic approaches such as Kalman filtering which provides an optimal estimation of hidden states of a system by analyzing observable measurements.

We hypothesize this facilitation underlies the highly robust target tracking observed in dragonflies. Therefore, a bio-inspired facilitation is proposed in this research project to enhance the performance of the existing bio-inspired models.

Moreover, these types of neurons have shown competitive selection of one target in presence of other distracters (Wiederman and O'Carroll, 2013). Electrophysiological recordings of CSTMD1 neuron show that irrespective of target size, contrast, or separation, this neuron selects one target from the pair and perfectly preserves the original response as if the distracter was not present (Wiederman and O'Carroll, 2013). These results bring insight to robust control of target pursuit in the presence of other distracters.

5.3.4 Insect Gaze Control

Studies of fly flight behavior show that they control the direction of flight along with their gaze direction through short and fast saccadic movements where their head and body turn independently (Van Hateren and Schilstra, 1999). This uncoupling of the eye from its support enables the insect to maintain the orientation of the gaze even when disturbances occur which affect its body. Moreover it reduces the temporal blurring effects and may promote ‘popout’ of a target against a background as a result of the high-pass nature of key stages of visual processing

During a pursuit, an insect has to control its forward velocity and distance to the target while fixating the target in the frontal visual field. Two different gaze control strategies have been seen among flying insects (Figure 3); tracking as described from male houseflies (Wehrhahn et al. 1982) during which a heading is calculated from the error angle between the target and the central axis of the pursuer's gaze (Land and Collett 1974, Wehrhahn et al. 1982); and intercepting as observed in dragonflies (Olberg et al. 2000) which involves the calculation of the future trajectory of the target to intercept its anticipated position. It was found that dragonflies use steering to minimize the movement of the prey's image on their retina in order to estimate the intersection of the target flight trajectory (Olberg et al. 2000). Using this strategy, dragonflies chase their target by flying directly to a point in front of the prey (Olberg et al. 2000). High prey capture rates in dragonflies seem to be related to the insect's ability to maintain its head oriented at a constant angle with respect to the visual field (Olberg et al. 2000). Although it is believed that the pursuit strategy in the dragonfly has a key role in its high catching rate, to date, the effect of different pursuit strategies in flying insects have not been investigated in a robotic platform.

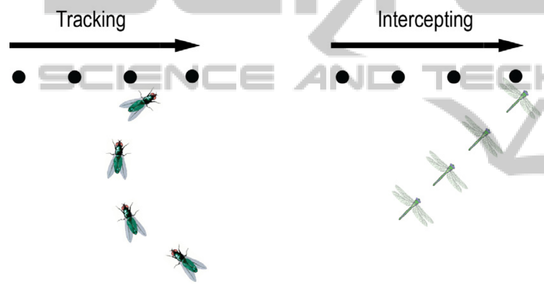

Figure 3: Two main flying insects' pursuit strategies.

6 METHODOLOGY

To achieve the objectives of this research project, both computational and experimental investigations will be conducted. The performance of the model under different conditions has initially been examined using computational simulation. In the next stage a robotic platform will be used to further investigate the performance of the model under different real world conditions (weather, sunlight, etc.).

6.1 Computational Methods

For the computational part of this project an extended version of the previously published ESTMD model (Wiederman et al., 2008) is used. The closed-loop pursuit block diagram presented in Figure 4 is the insect inspired detection and tracking model which is utilized in the simulations. Different stages of this model are described briefly in the following paragraphs.

In order to approximate the spectral sensitivity of fly photoreceptors that subserve motion processing (Srinivasan and Guy,1990) and optical blur of an insect compound eye, this model selects only the green channel of the RGB input image and applies a Gaussian spatial blur on it. The output signal goes through spatiotemporal bandpass filtering which includes centre-surround antagonism to remove redundant information in the image, which is inspired by the same mechanism in photoreceptors and large monopolar cells. Centre-surround antagonism is a spatial feature of LMC which enables edge detection and contrast enhancement. In the ESTMD model the centre-surround antagonism is implemented by convolving the image with a kernel which applies a negative weighting to the surrounding nearest-neighbor pixels.

The output of early visual processing (Figure 4) goes through half wave rectification which imitates the independent ON and OFF channels of insects by separating reverse polarities. Then each independent channel is processed via a fast adaptive mechanism. The fast adaptive mechanism is modeled by using a fast lowpass filter (τ=3 ms) when the input signal increases, and a slow lowpass filter (τ=70 ms) when it decreases. This adaptation process serves to inhibit repeating bursty inputs, such as noise. Both of the ON and OFF channels then undergo further centre-surround antagonism which helps to selectively tune the model to small sized targets.

The earlier version of the ESTMD model (Wiederman et al. 2008, Halupka et al. 2011) was only sensitive to dark targets. But for the purpose of this project, it has been modified to respond to both dark and light targets by delaying and multiplying the relevant contrast polarities (ON and OFF channels).

In this new computational model developed for this research project, the facilitation mechanism observed in the dragonfly CSTMD1 neuron is implemented by multiplying the output of the ESTMD model with a lowpass filtered version of a 'weighted map' dependent on the location of the winning feature but offset in the direction of target motion. This facilitation mechanism increases the chance of a repetitive winner to be the superior in the next time step by enhancing the area around the estimated location of the winning feature. The role of the lowpass filter time constant here is to control the period of the time that the facilitation matrix enhances the area around the winning feature. The location of the winning feature in the output of ESTMD model will be used as the target location and fed into saccadic pursuit algorithm to calculate

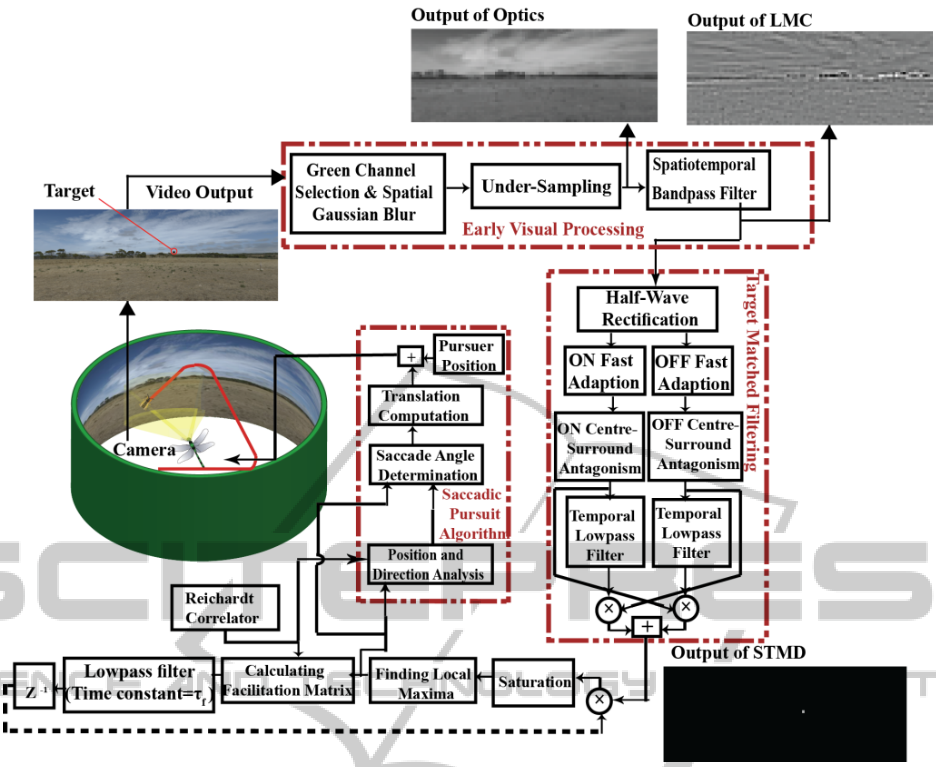

Figure 4: Overview of the closed-loop block diagram of the computational model for simulation and the output of each stage.

pursuer translation and rotation.

In order to simulate this computational model, the Simulink 3D Animation Toolbox was used to create a virtual world as the front-end for the bio-inspired target detection and pursuit control algorithm. A cylindrical arena with rendered natural panoramic images was used as a virtual environment (Figure 4). In order to move a target within this environment, randomized three dimensional paths with biologically plausible constraints on 'saccadic' turn angles have been generated. Moreover, the 3D Animation Toolbox provides the possibility of embedding 3D objects within this environment to act as occluding obstacles and foreground clutter.

Within the virtual reality model a viewpoint was mounted on the pursuer position in these simulations. The video output of this viewpoint was fed as an input to the detection and tracking closed-loop control model.

6.1 Experimental Methods

For the practical part of the project a large payload (70kg) all-terrain mobile robot developed by Clearpath Robotics™, Husky A200, will be used as the platform. This robot operates under Robotic Operating System (ROS). To test the tracking algorithm, a Ladybug®2, spherical digital video camera (Point Grey Inc.) will be integrated with the Husky to provide a 360° viewpoint of the environment. The camera control software works under a Windows server, while ROS is compatible with Ubuntu. To overcome this problem with conflicting OSs, a virtualization software package like VirtualBox is required to load multiple guest OSs under a single host operating-system (host OS). The output of the camera will be used as input to the target detection and tracking model and will be processed by on board computer (Apple Mac mini).

In the next stage, to test the active gaze control, a limited view point camera will be mounted on the robot using a real-time pan-tilt-zoom mechanism, Yorick, developed by the University of Oxford (Bradshaw et al. 1994) to actively control the camera gaze. In order to determine the global position and orientation of the robot, dGPS and IMU systems will be utilized. Moreover, IR sensors and possibly scanning LiDAR will be used to navigate the robot safely without accident. To test the ability of this robotic platform to track moving objects a remote control quadrotor helicopter will be used to navigate a small object, e.g. a ping-pong ball, in different environment and conditions (e.g. weather, sunlight).

Figure 5: The bio-inspired autonomous robot implements target detection algorithms derived from electrophysiological recordings.

7 EXPECTED OUTCOME

Due to the high target density and maneuverability, high clutter, low visibility arising from terrain masking, etc., ground target tracking presents unique challenges not present in tracking other types of targets. Despite the enormous effort and significant progress in the field of visual target tracking, the lack of a robust algorithm capable of tracking objects in the most complex environments is still evident. Moreover, most of the developed methods are computationally expensive and require high speed processors and high spatial resolution cameras. The recent studies of insect visual system and gaze control, suggests that an effective, real-time and robust bio-inspired method can solve the visual object tracking problem.

Therefore the expected outcome of this project is a ground robotic platform which can autonomously detect and track small moving objects in the most sophisticated environments. Moreover, this project is defined to not only contribute to progress of the active research areas which require robust tracking algorithms, but also to help raising new questions in physiology as well. A hardware implementation of the proposed tracking algorithm can reveal the limits of the underlying systems for real world application and raise new questions to investigate the solutions that have evolved in the insect neural system

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