Sensor optimization of camera direction for time-limited search performance

Jennifer Hewitt, Christopher Renshaw, Orges Furxhi, Li Zhang, Ronald Driggers

Jennifer Hewitt, Christopher Renshaw, Orges Furxhi, Li Zhang, Ronald Driggers, "Sensor optimization of camera direction for time-limited search performance," Proc. SPIE 12106, Infrared Imaging Systems: Design, Analysis, Modeling, and Testing XXXIII, 1210604 (27 May 2022); doi: 10.1117/12.2618124

Event: SPIE Defense + Commercial Sensing, 2022, Orlando, Florida, United States

Sensor optimization of camera direction for time-limited search performance

Jennifer Hewitt*[a], C. Kyle Renshaw[a], Orges Furxhi[b], Li Zhang[a], Ronald Driggers[c]
[a]CREOL, the College of Optics and Photonics, Univ. of Central Florida, 4304 Scorpius St, Orlando, FL, USA 32816; [b]IMEC USA, 194 NeoCity Way, Kissimmee, FL, USA; [c]Wyant College of Optical Sciences, Univ. Of Arizona, 1630 E. University Blvd, Tucson, AZ, USA, 85721

ABSTRACT

The time-limited search model was developed for military operations for evaluating human search performance as a function of time, originally using static imagery but later expanded to accommodate moving sensor situations. Previously, we introduced an application for using this moving sensor search model to optimize a forward-facing sensor look-down angle for a given forward vehicle speed. In this work, we build on the optimization model to accommodate sensors that may be pointed in any direction, using coordinate transforms. This allows us to determine probability of detection for a given target as a function of a more generalized camera pointing direction. While this methodology may be applied for any target of interest such as road potholes, tanks, or IEDs, here we determine probability of detection of a Burmese python against a grass background.

Keywords: Time-limited search, human vision, target detection

1. INTRODUCTION

Probability of task performance is regularly evaluated for electro-optic infrared (EOIR) systems in the U.S. Department of Defense for targets such as tanks, incendiary explosive devices, etc. Understanding how probability of task performance evolves with time is crucial for understanding how effective a system is for targeting. Probability of task performance as a function of time is even more clearly important in systems where the sensor is traveling in a scene rather than remaining static.

Time-limited task performance for a human observer using a static sensor to search for a static target is a relatively simply problem and was originally modeled at the Night Vision and Electronic Sensors Directorate (NVESD) and is summarized by the following equation:

$$P(t) = P_\infty \left(1 - e^{\frac{-(t-t_0)}{\tau}}\right), 0 \le t < \infty \tag{1}$$

in which P_∞ is the probability of a task being done correctly when the observer is given infinite time, t_0 is a time offset representing when the observer starts searching, and τ is the average search time[1]. The model becomes more complicated when the sensor is moving, requiring additional factors to be considered due to the changing position of both the target and scenery with time. The networked imaging sensors (NIS) model was developed to account for these scene changes by iterating the static model over many time intervals by recursion[2]. The nth time interval is defined by:

$$P_n(t) = \begin{cases} P_{n,0} + \left(P_{n,\infty} - P_{n,0}\right)\left(1 - e^{-\frac{\left(t-t_{n,0}\right)}{\tau_n}}\right), & t \ge t_{n,0}; P_{n,\infty} > P_{n,0} \\ P_{n,0} + 0, & t \ge t_{n,0}; P_{n,\infty} \le P_{n,0} \end{cases} \tag{2}$$

Infrared Imaging Systems: Design, Analysis, Modeling, and Testing XXXIII, edited by Gerald C. Holst, David P. Haefner, Proc. of SPIE Vol. 12106, 1210604
© 2022 SPIE · 0277-786X · doi: 10.1117/12.2618124

All terms in Eq. (2) are analogous to those in Eq. (1), with the addition of the iterative term $P_{n,0}$, which defines the probability of task performance carried over from the end of the previous time interval, making it the initial probability at the current time interval. To reduce Eq. (2) to the static sensor, static target case in Eq. (1), we may assume there is only one time interval and then set the iterative term $P_{n,0}$ to zero.

In past work[3], we conducted a human perception experiment that used static imagery of Burmese pythons in a cluttered grass background to determine probability of detection as a function of range to target for the static case, given by:

$$P_{\infty}(R)=\frac{\left(\frac{R_{50}}{R}\right)^{E}}{1+\left(\frac{R_{50}}{R}\right)^{E}} \tag{3}$$

where R_{50} is the target range at which probability of detection is 50%, and E is an empirically fitted exponent. We then applied these results to the NIS model to determine optimal downward looking angle for a given vehicle speed to maximize probability of detection[4]. The principal concept from that work was relating P_{∞} as a function of range to target in a static image to P_{∞} as a function of time in a moving sensor situation by calculating range to target as a function of time. In that work, we assumed the sensor was traveling with a fixed height and constant forward velocity, pointed along the path it traveled, which allowed for the optimization of sensor look-down angle for a given speed of travel. However, a more generalized mathematical approach is required when incorporating camera orientations that are not forward-looking. In this work, we incorporate camera matrix theory into the model we previously established for moving sensor with static target to optimize generalized camera looking angle for maximum probability of detection for a human observer.

2. THEORY

2.1 Generalized Camera Pointing Direction

The probability of detection model requires knowledge of target position and range in order to determine probability of detection. In our previous work in modeling detection from a moving sensor, we assumed the sensor was pointed along the path it traveled, only changing look-down angle. In that case, the geometry necessary to determine range to target is trivial and requires only basic trigonometry. However, in a system in which the sensor orientation may also be to the left or right of the "forward" direction of travel, or even rolled around its pointing axis, it is relatively complicated to determine where the target is in the sensor's field of view, let alone target range from the sensor.

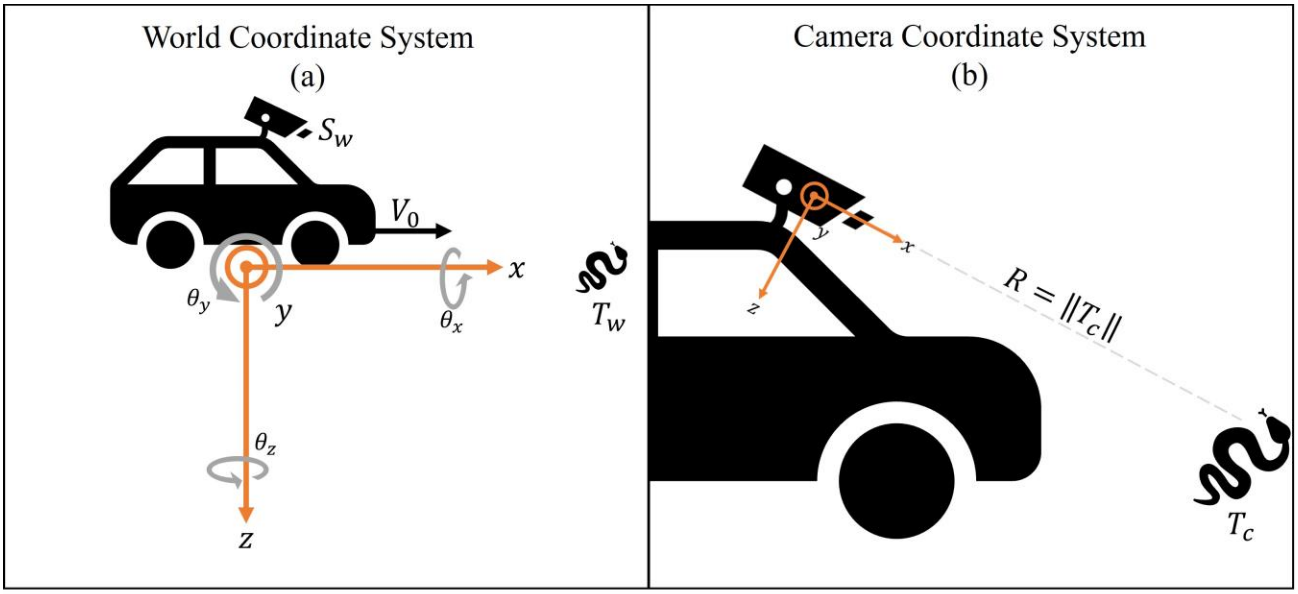

Figure 1. Illustrations defining (a) World coordinate system, and (b) Camera coordinate system.

To facilitate a better understanding of the problem, Figure 1 illustrates the two basic coordinate systems we must address to determine range to target. Figure 1(a) shows the World coordinate system (denoted by the subscript "w"), which is the more traditional coordinate system where the origin is located on the ground directly under the sensor location, and the x, y, and z axes are positive along the direction of the sensor path, to the right of the sensor path, and down, respectively. In this coordinate system, the sensor position S_w is stationary above the origin, and the target position T_w only changes along the axis the sensor is traveling according to the speed V_0 of the sensor. These positions at the nth time interval are:

$$S_W(t_n) = \begin{bmatrix} 0 \\ 0 \\ S_{w,z} < 0 \end{bmatrix} \tag{4}$$

$$T_w(t_n) = \begin{bmatrix} T_{w,x}(t_{n-1}) - V_0 dt \\ T_{w,y} \\ T_{w,z} \end{bmatrix} \tag{5}$$

Figure 1(b) shows the Camera coordinate system (denoted by the subscript "c"), for which the origin is positioned directly on the sensor, and the x, y, and z axes are positive along the camera's viewing axis, to the right of the viewing axis, and down from the viewing axis. In this coordinate system, the range to target is easily determined by the root-sum-squared of the target position components:

$$R = \sqrt{{T_{c,x}}^2 + {T_{c,z}}^2 + {T_{c,z}}^2} \tag{6}$$

In this coordinate system, we can also easily confirm whether the target is within the sensor's field of view at a given time interval by determining its position projected onto the sensor's detector array (using Image coordinate system subscript "i"):

$$T_i = \frac{f}{T_{c,x}} \begin{bmatrix} T_{c,y} \\ T_{c,z} \end{bmatrix} \tag{7}$$

While determining range to target and where it is in the sensor's field of view is simple using the Camera coordinate system, determining the target's position in this coordinate system requires a coordinate transformation from the World coordinate system. This coordinate transformation is summarized by:

$$T_c = R_{c\to w}^{-1}\left(T_w - S_w\right) \tag{8}$$

where $R_{c\to w}^{-1}$ is the inverse of a rotation matrix from the xyz-axes directions in the Camera coordinate system to the xyz-axes directions in the World coordinate system. This rotation matrix is given by:

$$R_{c\to w} = R_z R_y R_x = \begin{bmatrix} \cos(\theta_z) & -\sin(\theta_z) & 0 \\ \sin(\theta_z) & \cos(\theta_z) & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \cos(\theta_y) & 0 & \sin(\theta_y) \\ 0 & 1 & 0 \\ -\sin(\theta_y) & 0 & \cos(\theta_y) \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos(\theta_x) & -\sin(\theta_x) \\ 0 & \sin(\theta_x) & \cos(\theta_x) \end{bmatrix} \tag{9}$$

In this rotation matrix, θ_x, θ_y, and θ_z are the roll, pitch, and yaw rotations respectively of the sensor pointing direction about the axes in the World coordinate system. For example, if the sensor is pointed $15°$ down and $30°$ to the right of the forward axis of the vehicle (x-axis in the World coordinate system), the angles would be $\left[\theta_x \quad \theta_y \quad \theta_z\right] = \left[0° \quad -15° \quad 30°\right]$.

2.2 System-Specific Assumptions

In this work, this model is applied to the specific case of a Burmese python against a background of live foliage, but the same method can be used for other target/sensor systems. In this case we assume that the Burmese python is positioned in a loose coil on the ground, and that the ground itself is completely flat (i.e., no changes in elevation in the scene). This means in the World coordinate system, $T_{w,z} = 0m$. Also, for simplicity, we assume that for each modeled camera pointing direction, the target passes through the center of the sensor's field of view, thus controlling $T_{w,y}$ for each case.

The sensor used in this work is an Edmund Optics Vis-NIR camera with the specifications listed in Table 1. This sensor was selected to take advantage of the increased contrast between Burmese python skin and foliage in the near-infrared[3]. Assuming the Burmese python is $5\,ft$ long, the values for probability of detection as a function of range in Eq. (3) are $R_{50} = 18.3m$ and $E = 1.9$ [4]. The sensor is assumed to be positioned at a constant height $S_{w,z} = -2.04m$ above the ground and traveling along a straight path at a constant speed $V_0 = 5mph = 2.24\,\frac{m}{s}$. This path is considered the "forward" direction, or $\theta_z = 0°$ in the World coordinate system.

Table 1. Sensor specifications for Burmese python detection system.

Camera Model	EO-2223
Detector Pitch	5.5x5.5µm
Detector Array	2048x1088
Lens Focal Length	16mm
Filter	780nm cut-on longpass

3. RESULTS

Due to the assumptions made for this system, probability of detection would be symmetrical between all quadrants of the θ_z direction. Also, due to the assumption about target position being on the ground, the probability of detection for upward pointing directions ($\theta_y > 0$) are not modeled. For simplicity, we did not model for varied roll angle. For these reasons, we have modeled probability of detection for $-90° \le \theta_y < 0°$ and $-90° \le \theta_z \le 0°$ and $\theta_x = 0°$.

Probability of detection as a function of θ_z and θ_y for this system is plotted in Figure 2. Across all yaw angles θ_z, there is a clear peak in probability of detection. The optimal downward pitch angle was determined to be between $-23° \le \theta_y \le -17°$ in all cases, with the absolute maximum probability of detection being 85.7% located at pointing angle $\left[\theta_y \quad \theta_z\right] = \left[-19° \quad -31°\right]$.

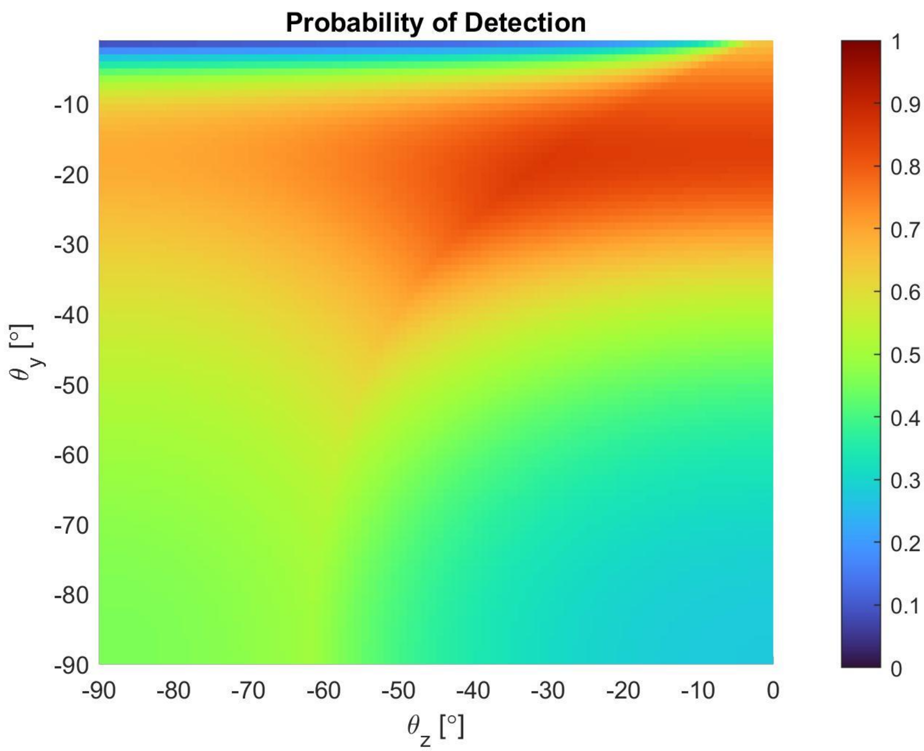

Figure 2. Probability of detection for varied camera pointing directions.

Figures 3 and 4 plot the total time the target is in the sensor's field of view and the average range to target while it is in the field of view, respectively, as functions of θ_z and θ_y. Both of these figures show that time on target and average range to target generally increase as the sensor looking angle goes to forward and horizon. In the θ_y domain, this makes intuitive sense; as the sensor pitch angle becomes shallower, the area of ground covered within the sensor field of view increases. This allows the target to remain in the sensor field of view for a longer period of time. However, during that extra time, the target is further away from the sensor on average.

As Eq. (1) and Eq. (2) imply, probability of detection increases with time. This means in Figure 2, at pitch angles that are steeper than optimum, time on target is the driving component that increases probability of detection. Conversely, Eq. (3) shows that probability of detection if given infinite time decreases as range increases. From this we conclude that at pitch angles that are shallower than optimum, longer ranges to target outweigh the benefits derived from increased time on target.

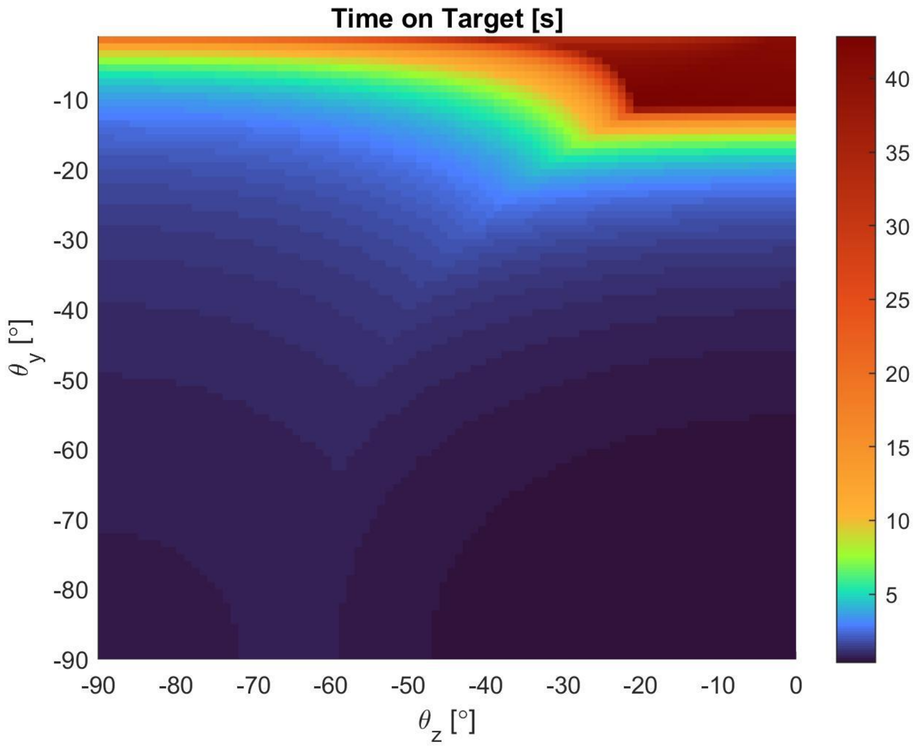

Figure 3. Time on target for varied camera pointing directions.

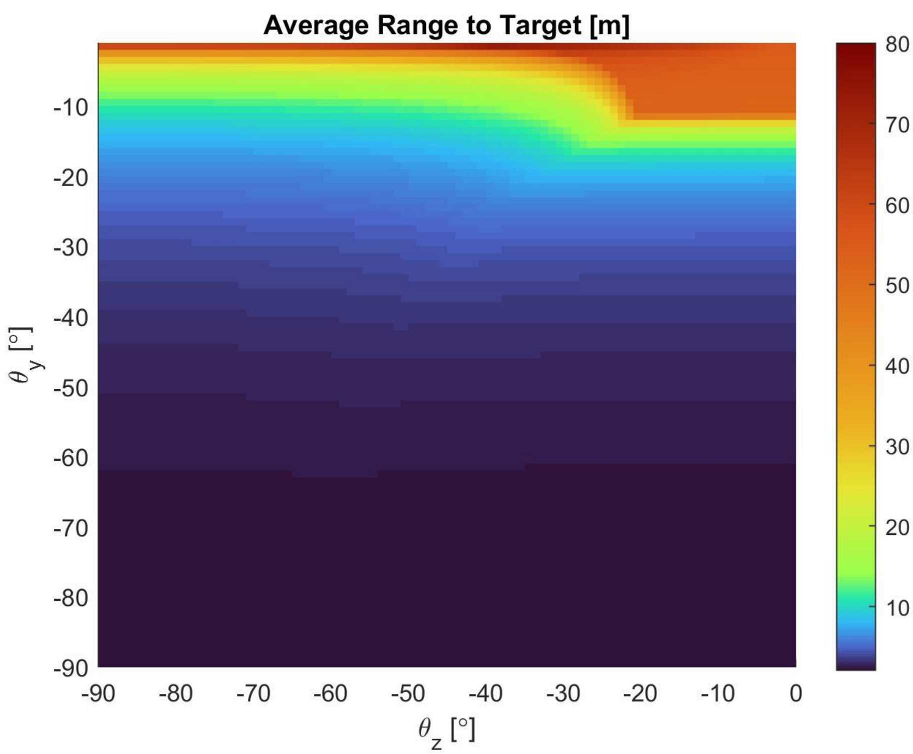

Figure 4. Average range to target for varied camera pointing directions.

4. DISCUSSION

Figures 2-4 share a common slope discontinuity among them, which results in a minor peak that arcs across each plot. This discontinuity is a result of the rectangular shape of the detector array and marks the case in which the target passes along the diagonal of the array. This results in a radial maximum for all plots, centered at $\begin{bmatrix}\theta_y & \theta_z\end{bmatrix} = \begin{bmatrix}-90° & 0°\end{bmatrix}$, with the arc's circularity dependent on the ratio of the array dimensions.

In this work, to model probability of detection, the target was placed at a set initial position in the World coordinate system, $T_{w,x} = 100m$. We acknowledge that this is well within the sensor field of view for looking angles that approach $\begin{bmatrix}\theta_y & \theta_z\end{bmatrix} = \begin{bmatrix}0° & 0°\end{bmatrix}$ and results in an artificial plateau in this region for Figures 3 and 4. While we could place the initial position of the target further out than modeled here, there will be cases in this region of looking angles where the sensor field of view includes the horizon and not just the ground. This would mean the target would theoretically be in the sensor field of view at $R = \infty$, which is infeasible to account for. Considering the average range to target in this region is well beyond R_{50} for this system, it is unlikely that starting the target further away than modeled here would result in a new absolute maximum probability of detection for the overall system.

5. CONCLUSION

By incorporating coordinate transformations between the traditional World and Camera coordinate systems into the time-limited moving sensor model, we have shown that sensor pointing angle can be optimized for maximum probability of detection. The two main variables that determine optimal pointing angle are time in which the target is in sensor field of view, and the average range to target during that time. For most pointing angles, probability of detection is shown to be primarily dependent on time on target. However, at shallow downward-looking angles, while the target is in the sensor field of view for longer durations, the range to target during most of that time is comparable to or longer than R_{50} and results in reduced probability of detection overall. While these results have been applied to detection of Burmese pythons, this methodology can also easily be applied to search modeling for other targets of interest such as IEDs, tanks, etc. from a moving sensor.

REFERENCES

[1] Friedman, M. and Moyer, S., "Initial verification of an analytical model for target acquisition of multiple moving targets using multiple moving sensors," U.S. Army, NVESD (2014).

[2] Friedman, M. Choi, H. S., Cha, J., and Reynolds, J., "Validating an analytical technique for calculating detection probability given time-dependent search parameters," Proc. SPIE 8355, 835511 (2012).

[3] Hewitt, J., Furxhi, O., Renshaw, C. K., and Driggers, R., "Detection of Burmese pythons in the near infrared vs. visible band," Applied Optics 60(17), 5066-5073 (2021).

[4] Hewitt, J., Renshaw, C. K., Furxhi, O., and Driggers, R., "Optimizing sensor design using a time-limited search model of moving sensor," Proc. IEEE RAPID, 1-2 (2021).