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INDIRECT FIRE TARGET STATE ESTIMATION AND PREDICTION USING AERIAL SCOUT VEHICLES

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ABSTRACT

It is well known that target state estimation and prediction methods can have a substantial influence on the outcome of long range, precision-oriented engagements. Due to this fact, a collection of techniques and algorithms have been developed for the purpose of minimizing the delivery error caused by target motion over the flight time of a munition. These legacy compensation techniques have typically come from direct fire, accuracy-oriented assets such as main battle tanks and attack helicopters. However, with the proliferation of unmanned vehicles in the battle space, the target state estimation and prediction capabilities could be extended into the indirect fire domain. The work conducted within examines the challenge of utilizing a reconnaissance drone partnered with a decoupled weapon platform to track a target, predict its motion, and calculate a lead. The information presented within establishes the framework required to enable this capability, develops the individual solution components, and addresses the practical concerns of the implementation. Finally, modeling and simulation is utilized to validate the proposed methods and to draw conclusion on the feasibility of the specified approach.

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1. INTRODUCTION

Direct fire weapon platforms are defined by the presence of a line of sight (LOS) between the shooter and target. This construct is an essential part of the fire control system as the targeting, prediction, and ballistics functions are all tied to this frame of reference. In legacy platforms, the use of the LOS enabled the development of efficient fire control routines, but the requirement limited the weapon's capabilities as visual contact had to be established before the fire control kill chain could be completed. However, with the introduction of unmanned aerial scout vehicles, the LOS could be moved off the main platform and onto a remote asset. In practice, such an agent would stream information about the target's state to a ground-based weapon, which would utilize the data sequence to engage the threat. From the fire control perspective, this type of functionality is more challenging and involved than a LOS engagement and the difficulty of the task only increases when the threat is moving. These complications come from multiple regimes such as data transmission, sensor precision, and algorithm complexity. The work presented within only addresses a small portion of the overall effort required to bring the idea to fruition, namely the target state estimation and prediction aspect of the problem at hand. Nevertheless, the effort is a small step towards the complete solution.

2. BACKGROUIND

The requirement for a weapon system to engage a moving threat is not new. In fact, direct fire weapon platforms have boasted this capability for decades. As a starting point, these established solutions are worth examining as they provide a foundation for the remote implementation.

Traditional approaches for calculating a target lead typically come in one of three variations. These are the Infantry method [1], the Abrams method [2] and the Apache method [2]. The Infantry method is simple; the shooter evaluates the sight picture to determine the target's velocity and utilizes a stadia reticle to estimate distance. Using these details, the rifleman aims a precalculated amount ahead of the target. The lead is based on a predetermined number of body widths specified within doctrine. This method is less accurate than the other implementations and does not account for several relevant variables within an engagement, but it easy to implement and does not require any specialized equipment. Furthermore, the technique does not need to be precise as the miss distance of the first shot is used to correct the initial lead estimate. Infantry will typically fire multiple rounds at a single target and therefore the success of the first shot is not as critical as it is in precision-oriented systems. The advantage of the infantry solution is that the technique enables a rough form of state estimation with minimal fire control components.

In contrast to the infantry method, the Abrams solution employs a dedicated algorithm for calculating a target lead. This technique is based on the slew rate of the sight and requires the gunner to track the target with the reticle while the computer system estimates the parameter. The distance to target is obtained from the laser range finder and the time of flight is calculated using a ballistic algorithm. From these three pieces of information, the angular lead is found. This implementation is efficient and quite robust but is limited to engagements in a two-dimensional plane with flat fire trajectories.

The Apache solution overcomes the constraints of the Abrams method as the attack helicopter is required to engage targets moving in all three spatial coordinates. To achieve this task, the lead calculations leverage a Kalman filter paired with a constant velocity model. Much like the Abrams, the gunner is required to track the target as the filter settles but this approach estimates the target velocity rather than the sight's angular rates. The system then utilizes the motion model and time of flight to predict the future target position. The Apache solution is the most capable and robust of the three options.

The Infantry, Abrams, and Apache methods of predicting target state share two attributes. The first is that the techniques are reliant on the LOS and the second is that the algorithms are simplistic by modern standards. These characteristics are a product of the design requirements and computational restrictions present at the time of development.

However, given that curent weapon systems are not subject to the same constraints as the legacy solutions were, the lead estimation methods could be updated to remove the dependence on the LOS while simultaneously increasing the performance of the algorithms. Consequently, the effort described within strives to meet these two objectives.

3. PROBLEM STATEMENT

In order to move from a nebulous concept to a concrete implementation, the work presented makes several assumptions about the form factor of the UAV, sensors, and method of employment. The first of these assertions is that the aerial forward observer (scout) is assumed to be a small, lightweight quadcopter or fixed wing drone outfitted with a gimbaled sight package dedicated to the targeting mission. The targeting sensor is assumed to include a high-resolution camera paired with a laser range finder capable of reporting the distance to the target at the same rate as the optic is producing imagery. During a mission, a pilot or auto tracking software is assumed to keep the sight package aligned to the target within some realistic bounds. Additionally, the target is assumed to be present in open terrain and can be easily discerned from the background. The given algorithms do not make any attempts to separate target data returns from background clutter or other objects in the scenery. The scout is also assumed to be fitted with inertial navigation and global positioning sensors. The data generated by these components is assumed to be reliable, noise free, and accurate. Finally, the targeting systems is assumed to produce a new and complete set measurements collected at every computational cycle with the fire control loop running at a minimum rate of 30 Hz.

On the target side, only a few assumptions are required. The first of these is that the target follows a path dictated by basic kinematics and changes in state are gradual relative to the update rate. The target is allowed to accelerate in a straight line but generally keeps a constant velocity during turns. In terms of path characteristics, the enemy is not aware they are being targeted and are therefore not taking deliberate evasive actions. Although such maneuvers are of considerable interest, the extension of the baseline solution to this domain is left for future work. The current development only considers basic target motion.

With regard to the weapon system, the asset is assumed to be placed at a location that does not permit an LOS engagement but effortless communication with the scout is possible. The platform is outfitted with inertial and global position sensors and can estimate its own state. The solution provided does allow the weapon to be mounted to vehicle and thus move – move scenarios are possible. Regardless, the weapon does not contain any type of targeting sensor and relies purely on the data communicated by the scout to complete the engagement.

The described conditions and assumptions are representative of what could be expected in a demonstration environment using current technology. Further consideration would need to be given to advance the solution from the experimental domain to a deployable system. For purposes of this document, only the outlined engagement scenario is considered.

4. PROPOSED SOLUTION

The proposed solution described within leverages the given problem bounds and sensor assumptions to derive a processing path for completing the firing mission. The enabling concept behind the approach is that target motion is specified and exchanged in an earth-fixed reference frame. The algorithm for completing the fire control task consists of 6 steps, which are as follows.

1. Convert scout sensor data to local North, East, Down (NED) frame.
2. Convert the NED grid to Earth Center Earth Fixed (ECEF) coordinates and transmit to weapon platform.
3. Receive ECEF data stream and convert to weapon-centered NED.
4. Apply a filter utilizing a Horizontal Constant Turn model to received data.
5. Calculate ballistic solution.
6. Leverage motion model to predict the change in target position over the time of flight of the munition.

The important point to note in the outlined processing path is that the scout and weapon local NED frames have disparate origins. The frames may share a common orientation, but there are significant distances between the datums being utilized to measure distance. Hence the need to the convert variables to the common ECEF system.

It should be noted that the methods utilized to complete the outlined subtasks are taken from literature. The unique contribution of the work being presented is the selection, augmentation, and assembly of the components required to produce the required results.

4.1. Convert Solution to a Local NED Coordinate

The first step in the processing chain is to convert the drone's sensor data into a target position and velocity within the local North, East, Down (NED) reference frame. The formulas required to complete the task are given in equations (1-3).

$$[R_{\phi\theta\psi}] = [A_1 \quad B_1 \quad C_1] \tag{1}$$

$$A_1 = \begin{bmatrix} c(\psi)\,c(\theta) \\ -s(\psi)\,c(\phi) + c(\psi)\,s(\theta)\,s(\phi) \\ s(\psi)\,s(\phi) + c(\psi)\,s(\theta)\,c(\phi) \end{bmatrix}$$

$$B_1 = \begin{bmatrix} s(\psi)\,c(\theta) \\ c(\psi)\,c(\phi) + s(\psi)\,s(\theta)\,s(\phi) \\ -c(\psi)\,s(\phi) + s(\psi)\,s(\theta)\,c(\phi) \end{bmatrix}$$

$$C_1 = \begin{bmatrix} -s(\theta) \\ c(\theta)\,s(\phi) \\ c(\theta)\,c(\phi) \end{bmatrix}$$

$$T_{EL} = [r, 0, 0]^T + O_{EL-LRF} \tag{2a}$$

$$T_{AZ} = [R_{EL}]^T T_{EL} + O_{AZ-EL} \tag{2b}$$

$$T_{EGI} = [R_{AZ}]^T T_{AZ} + O_{EGI-AZ} \tag{2c}$$

$$T_{NED} = [R_{EGI}]^T T_{EGI} \tag{2d}$$

$$V_{NED} = \frac{T_{NED}(n) - T_{NED}(n-1)}{t(n) - t(n-1)} + [R_{EGI}]^T V_{EGI} \tag{3}$$

Equation (1) is the rotation matrix used to convert vectors between coordinate systems. ψ, θ, ϕ are the yaw, pitch, and roll of the scout vehicle. To be more specific, they are intrinsic rotations based on the Euler angle sequence of yaw, pitch, then roll when moving from an inertial to a rotating coordinate frame. $c(\cdot)$ and $s(\cdot)$ are the sine and cosine operations, respectively.

Equation (2) describes the process of converting the targeting sensor data to a NED grid. r is the distance between the laser range finder and target. O_{EL-LRF} is the offset between the sight elevation gimbal and the LRF, O_{AZ-EL} is the distance between the sight AZ and EL gimbals, and O_{EGI-AZ} is the distance between the sight azimuth and the aircraft's center of rotation or armament datum line. Finally, the R matrices refer to the construct shown in equation (1) with the identified values inserted for roll, pitch, and yaw.

Equation (3) is the numerical derivative of the results of Equation (2) and is used to estimate velocities. It is important to note that the right most term represents aircraft speed converted to the inertial frame. This component is critical as it enables the formula to produce ground referenced estimates rather than relative velocities. Given a means of completing the first subtask, the next step is to convert the results to a global system.

4.2. Convert NED Grid to Earth Centered Earth Fixed Coordinates

Once the results of equation (2-3) are obtained, the next step in the processing sequence is to convert the NED target data to ECEF triplets. This task is accomplished via equation (4-5).

$$n = \frac{a}{\sqrt{1 - e^2 \sin^2(\phi)}} \qquad (4a)$$

$$S_X = (h + n)\cos(\phi)\cos(\lambda) \qquad (4b)$$

$$S_Y = (h + n)\cos(\phi)\sin(\lambda) \qquad (4c)$$

$$S_Z = (h + n - e^2 n)\sin(\phi) \qquad (4d)$$

Equation (4) is used to convert the scout's position from a Latitude, Longitude, and Altitude (LLA) coordinate set to ECEF coordinates. Here, λ is the longitude, ϕ is the geodetic latitude, a is the semi-major axis, e^2 is the squared eccentricity of the ellipsoid, and h is the height above the ellipsoid or the altitude.

Next, equation (5) is utilized to move the target vector and velocity from the NED system to the ECEF system.

$$\begin{bmatrix} \Delta T_X \\ \Delta T_Y \\ \Delta T_Z \end{bmatrix} = \begin{bmatrix} -\mathrm{c}(\lambda_s)\,\mathrm{s}(\phi_s) & -\mathrm{s}(\lambda_s) & -\mathrm{c}(\lambda_s)\,\mathrm{c}(\phi_s) \\ -\mathrm{s}(\lambda_s)\,\mathrm{s}(\phi_s) & \mathrm{c}(\lambda_s) & -\mathrm{s}(\lambda_s)\,\mathrm{c}(\phi_s) \\ \mathrm{c}(\phi_s) & 0 & -\mathrm{s}(\phi_s) \end{bmatrix} \begin{bmatrix} T_N \\ T_E \\ T_D \end{bmatrix} \quad (5a)$$

$$\begin{bmatrix} V_X \\ V_Y \\ V_Z \end{bmatrix} = \begin{bmatrix} -\mathrm{c}(\lambda_s)\,\mathrm{s}(\phi_s) & -\mathrm{s}(\lambda_s) & -\mathrm{c}(\lambda_s)\,\mathrm{c}(\phi_s) \\ -\mathrm{s}(\lambda_s)\,\mathrm{s}(\phi_s) & \mathrm{c}(\lambda_s) & -\mathrm{s}(\lambda_s)\,\mathrm{c}(\phi_s) \\ \mathrm{c}(\phi_s) & 0 & -\mathrm{s}(\phi_s) \end{bmatrix} \begin{bmatrix} V_N \\ V_E \\ V_D \end{bmatrix} \quad (5b)$$

In equation (5), the λ and ϕ values are, again, the scout vehicle's longitude and latitude. The output of EQ 5a is the change in target position rather than the absolute target position within the ECEF frame. EQ 5b produces the target velocity in ECEF coordinates. To obtain the absolute ECEF target position, equation (6) is used.

$$T_{XYZ} = S_{XYZ} + \Delta T_{XYZ} \qquad (6)$$

Equation (6) states that the target XYZ coordinate is the sum of the scout vehicle XYZ position and the targeting vector between the scout and target converted to the ECEF frame. The result of equation (6) and equation (5b) can now be transmitted over the network to the weapon platform.

4.3. Transform Data Stream to Weapon NED.

Once the target position and velocity is received by the weapon platform, the data needs to be reverted to the local NED system. To accomplish this task, first equation (4) is used to convert the weapon position to the ECEF system, producing W_{XYZ}. Next, equation (7) is used to find the distance between the weapon and target in ECEF.

$$T_{XYZ_w} = W_{XYZ} - T_{XYZ} \qquad EQ\ 7$$

Equation (8) is then used to convert the ECEF targeting vector and velocity to the local NED grid.

$$\begin{bmatrix} T_N \\ T_E \\ T_D \end{bmatrix} = \begin{bmatrix} -(\lambda_w)\,\mathrm{s}(\phi_w) & -\mathrm{s}(\lambda_w)\,\mathrm{s}(\phi_w) & \mathrm{c}(\phi_w) \\ -\mathrm{s}(\lambda_w) & \mathrm{c}(\lambda_w) & 0 \\ -\mathrm{c}(\lambda_w)\,\mathrm{c}(\phi_w) & -\mathrm{s}(\lambda_w)\,\mathrm{c}(\phi_w) & -\mathrm{s}(\phi_w) \end{bmatrix} \begin{bmatrix} T_{X_w} \\ T_{Y_w} \\ T_{Z_w} \end{bmatrix} \quad (8a)$$

$$\begin{bmatrix} V_N \\ V_E \\ V_D \end{bmatrix} = \begin{bmatrix} -(\lambda_w)\,\mathrm{s}(\phi_w) & -\mathrm{s}(\lambda_w)\,\mathrm{s}(\phi_w) & \mathrm{c}(\phi_w) \\ -\mathrm{s}(\lambda_w) & \mathrm{c}(\lambda_w) & 0 \\ -\mathrm{c}(\lambda_w)\,\mathrm{c}(\phi_w) & -\mathrm{s}(\lambda_w)\,\mathrm{c}(\phi_w) & -\mathrm{s}(\phi_w) \end{bmatrix} \begin{bmatrix} V_X \\ V_Y \\ V_Z \end{bmatrix} \quad (8b)$$

Note that the weapon latitude and longitude are used to make the conversion.

Equations (1-8) produce a stream of target positions and velocities in the weapon system's local NED frame. This data can now be utilized by the weapon platform to predict the motion of the target.

4.4. Apply Filter

The first step in making a target state prediction is filtering of the targeting data.

Here, an abbreviated strategy is utilized. Most routines used for this type of task leverage a Kalman filter with a chosen motion model or an IMM filter [4-10]. Past work in this domain revealed that such complex solutions are not necessary as the given application does not benefit from the advanced features of these solutions [5]. Thus, the strategy recommended here is to utilize a variable weight α-β-Γ like filter [11]. The advantage of this solution is that method offers near IMM filter performance (in the given application only) for a fraction of the complexity and processing power. The recommended filter equations are given in equation (9).

$$X_k = [p_n \ \ v_n \ \ a_n \ \ p_e \ \ v_e \ \ a_e \ \ p_d \ \ v_d \ \ a_d]^T \quad (9a)$$

$$X_k^P = \begin{bmatrix} A_{ct} & O & O \\ O & A_{ct} & O \\ O & O & A_{ca} \end{bmatrix} [X_{k-1}] \quad (9b)$$

$$A_{ct} = \begin{bmatrix} 1 & \frac{\sin(\omega\Delta t)}{\omega} & (1-\cos(\omega\Delta t))/\omega^2 \\ 0 & \cos(\omega\Delta t) & \frac{\sin(\omega\Delta t)}{\omega} \\ 0 & -\omega\sin(\omega\Delta t) & \cos(\omega\Delta t) \end{bmatrix} (9c)$$

$$A_{ca} = \begin{bmatrix} 1 & \Delta t & \frac{\Delta t^2}{2} \\ 0 & 1 & \Delta t \\ 0 & 0 & 1 \end{bmatrix} \quad (9d)$$

$$X_k = \mathrm{X}_k^{\mathrm{p}} + K_k \circ I_k \quad (9e)$$

$$I_k = [A_{9f} \quad B_{9f} \quad C_{9f}] \quad (9f)$$

$$A_{9f} = \begin{bmatrix} T_{NED_w}(1) - X_k^p(1) \\ T_{NED_w}(2) - X_k^p(4) \\ T_{NED_w}(3) - X_k^p(7) \end{bmatrix}$$

$$B_{9f} = \begin{bmatrix} V_{NED_w}(1) - X_k^p(2) \\ V_{NED_w}(2) - X_k^p(5) \\ V_{NED_w}(3) - X_k^p(8) \end{bmatrix}$$

$$C_{9f} = \begin{bmatrix} V_{NED_w}(1) - X_k^p(2) \\ V_{NED_w}(2) - X_k^p(5) \\ V_{NED_w}(3) - X_k^p(8) \end{bmatrix}$$

$$K_k = [A_{9g} \quad A_{9g} \quad A_{9g}]^T \quad (9g)$$

$$A_{9g} = [k_{p_n} + \beta_{\mathrm{p}} \quad k_{v_n} + \beta_{\mathrm{v}} \quad 1 - (k_{a_n} + \beta_{\mathrm{a}})]$$

$$k_{p_n} = k_{p_{n-1}} - \frac{k_{p_{n-1}}}{\alpha_p} \quad EQ\ 9h$$

$$k_{v_n} = k_{v_{n-1}} - \frac{k_{v_{n-1}}}{\alpha_v} \quad EQ\ 9i$$

$$k_{a_n} = k_{a_{n-1}} - \frac{k_{a_{n-1}}}{\alpha_a} \quad EQ\ 9j$$

Equation (9) is a combination of components from multiple sources [5,8,9,11] and represents a variable weight $\alpha - \beta - \Gamma$ filter implementing a horizontal turn model. The distinction between this set of equations and the typical Kalman system is that the gain is controlled directly rather than from the assumably known statistics of the data stream.

In equation (9a), p, v, a are the filtered position, velocity, and acceleration that make up the target state X_k. Within equation (9b,c,d), A_{ct} is the state transition matrix for a constant turn model and A_{ca} is the transition matrix for a constant acceleration model. A is recomputed at every filter cycle and relies on ω, which is the estimated turn rate and is equal to $\|a\|/\|v\|$. Equation (9e) updates the target state using the gain matrix K_k and innovation vector I_k. The innovation is difference between the measured and predicted state and is described via equation (9f). Equation (9f) assumes only measurements of position at the weapon station (T_{NED_w}) and velocity (V_{NED_w}) are available. Equation (9g) describes the gain vector, which is recomputed at every filter cycle via equation (9h,i,j). The constants $\beta_p, \beta_v, \beta_a$ control the steady state gain for position, velocity, and acceleration while $\alpha_p, \alpha_v, \alpha_a$ control the rate at which the gains move from the initial to the steady state values. Equation (9h,i,j), evolves the position and velocity gains from an initial value of 1 to β while the acceleration is initialized to 0 and raises to a steady state value. Figure 1 illustrates the trend.

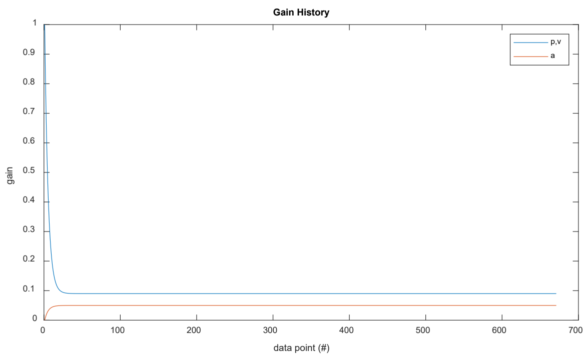

Figure 1: Position, Velocity, and Acceleration Gains vs Number of Data Points.

The gains shown in Figure 1 were chosen in the manner depicted as this configuration was found to work well within the example problem being studied. Large initial values for position and velocity and near zero acceleration gains allow the filter to ascertain an initial estimate of the target state with the first set of readings. Then, as the data stream continues, the filtering comes online and steady state performance is achieved.

The sequence of equations presented up to this point is used to transfer the position and velocity measurements taken by the arial scout vehicle to the weapon system's frame of reference. The resulting state X_k contains the information required to compute a ballistic solution and make a lead prediction.

4.5. Calculate Ballistic Solution

Given a state vector that contains the position of the target in the NED frame, the ballistic process is now able to calculate a firing solution consisting of the weapon azimuth and elevation required for the projectile to intercept the target along with Time of Flight (TOF) of the munition. Upon initialization, the firing solution will be computed using the target's current position with no lead estimation. This result produces a preliminary TOF that can be utilized to update the target's position on the next set of computations. This idea is captured in equation (10).

$$[AZ_k, EL_k, TOF_k] = B(A_{10}, B_{10}, C_{10}) \qquad EQ\ 10$$

$$A_{10} = X_k(1) + \Delta p_n(tof_{k-1})$$
$$B_{10} = X_k(4) + \Delta p_e(tof_{k-1})$$
$$C_{10} = X_k(7) + \Delta p_d(tof_{k-1})$$

In equation (10), B() is the ballistic process and represents a set of algorithms utilized to solve for the weapon orientation and time of flight. The inputs into the algorithm are the NED coordinates of the target represented by the arguments into the function. Each component of the future position vector consists of the current position taken from the state vector and a change in position computed from the motion model using the previous estimate of TOF. These quantities are represented via $\Delta p_{n,e,d}(tof)$ and are computed in the next section.

4.6. Predict Change in Target Position

Determining the change is target position over the time of flight of the munition is accomplished by evolving the motion model outlined in equation (9). The formulas are advanced recursively through time by the number of steps required to equal the TOF. This process is captured in equation (11).

$$\Delta p_{n,e,d}(tof) = \mathrm{X}_i^{\mathrm{P}} - X_k \qquad (11a)$$
$$\mathrm{X}_i^{\mathrm{P}} = A\mathrm{X}_{i-1}^{\mathrm{P}}\ for\ i = 1\ to\ \lfloor tof/\Delta t \rfloor \qquad (11b)$$

Equation (11a) establishes that change in target position is the difference between the current target state and the predicted state evolved to the delivery time of the munition. Equation (11b) indicates that the predicted state vector (X^p) is processed through the state transition matrix several times with each new state estimate being built from the last. The important point to observe here is that A, then, is recalculated at each iteration with ω being estimated from the previous prediction. Running this loop until the necessary number of steps forward have been taken produces the required change in position.

Equations 1 through equation 11 represent one complete processing cycle of the proposed solution.

5. Validation via Simulation

Validation of the presented concepts was achieved by examining several engagement scenarios with varying levels of complexity. Initially, only constant state maneuvers were considered. Later trials varied the magnitudes of the key variables throughout the trial eventually culminating in compound motion tracks with evolving parameters. The objective of this approach was to methodically exercise the variables outlined in the preceding segment and look for systematic departures from the known paths. One of the most complex engagements examined is illustrated in Figure 2.

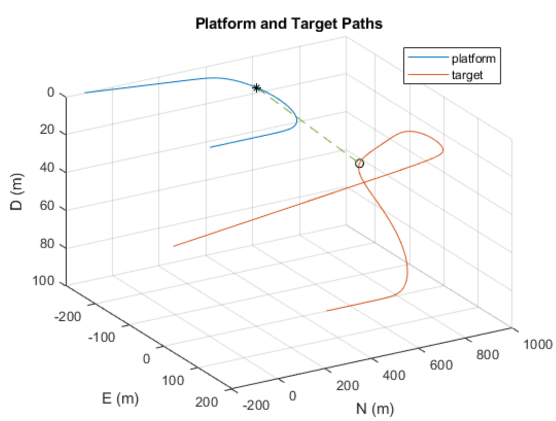

Figure 2: Scout and Target Motion Paths. Weapon position is not shown.

Figure 2 shows the scout vehicle moving along the blue path and the target moving along the orange. The image is a still frame from the animation where the "*" marks the scout's current position and "o" marks the target. The LOS ray (green dashed line) between these two points confirms that the scout's roll, pitch, yaw, azimuth, elevation, and range variables (inputs in equation 1 – 3) are correct as errors in these variables or processing would cause the line of sight to point at a location other than the target.

Next, to ensure the correct processing of Latitude, Longitude, and Altitude (LLA), the flight paths of the scout and target were plotted in Google Earth.

Figure 3: Scout and Target Flight Paths Mapped

Figure 3 shows that the scout and target paths illustrated in Figure 2 were successfully transformed to LLA coordinates. This task was necessary to assure the GPS inputs.

Next, the data shown in Figure 2 and Figure 3 was utilized as input into equations (4-6).

For the next set of calculations, the weapon was placed at the starting location of the scout path. The data stream reported by the scout was used along with the weapon location within equations (7-8) to produce a weapon centered NED vector representing the location of the target from the weapon platform. This was done for all points in the flight path. The results of equation (8) are shown in Figure 4.

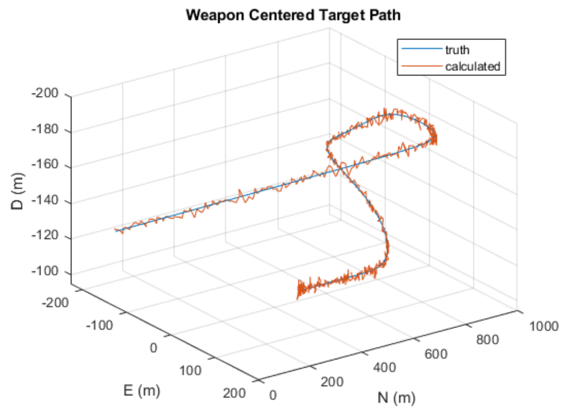

Figure 4: Weapon Centered Target Path (NED)

Figure 4 overlays the results of equation (8) over the truth data shown in Figure 3 and Figure 2. The calculated path includes noise from the sight azimuth and elevation gimbals as well as the laser range finder. These disturbances were added to provide a more realistic set of data to process through the filter in equation (9). The results of the filtering process are given in Figure 5.

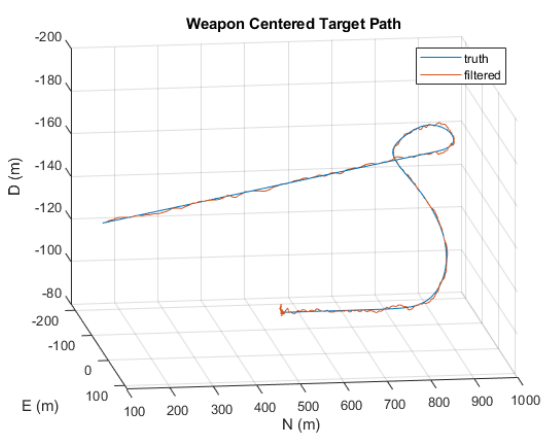

Figure 5: Filtered Weapon Centered Target Path (NED)

The smooth and aligned filtered signal given in Figure 5 shows that equation (9) was able to remove most of the noise present in the data. The filter constants were tuned to balance the reduction in noise while also remaining responsive enough to accommodate the dynamics of the target maneuver. Given this result, equation (11) was then used to predict the target position for a 3 second TOF. Equation (10) was not exercised as that would involve importing a selected ballistic solver, choosing weapon characteristics, and specifying other variables that would ultimately add no value to the end result. The 3 second TOF selected was seen as being representative of the expected delivery time for the family of munitions of interest at extended ranges. Processing the data shown in Figure 5 using the 3 second TOF produces the prediction results displayed in Figure 6.

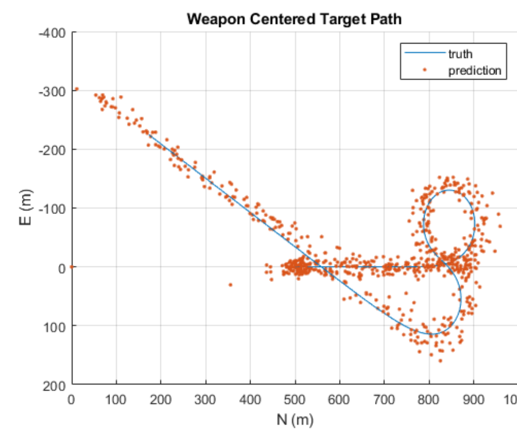

Figure 6: Weapon Centered Target Path Prediction (NED)

Figure 6 shows that the centerline of the predictions follows the truth target path. The scatter is a product of the noise introduced into the sensor data. The important characteristic to notice is that the rough center of the prediction path follows the true path closely, indicating the absence of systematic departures and confirming that the response lag to the maneuvers has been mostly eliminated. The magnitude of the scatter is troubling as the individual prediction errors are significant enough to miss most targets of interest. Nevertheless, this characteristic could be eliminated with additional work. However, such an effort is beyond the limits of the current discussion. Figure 7 is only shown to substantiate the stated claim.

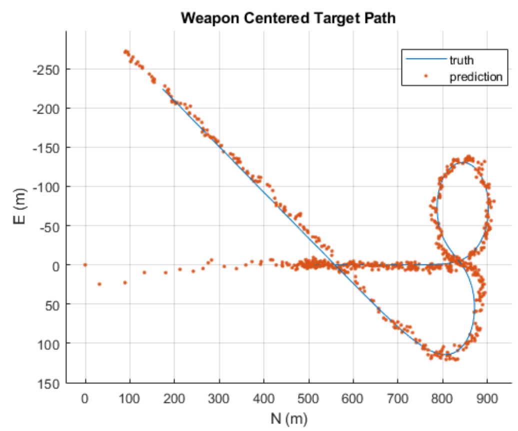

Figure 7: Improved Weapon Centered Target Path Prediction (NED)

6. Conclusion

The work presented within identified the sensors, signals, and sequence of mathematical operations needed to calculate a lead for a weapon station receiving targeting information from a remote reconnaissance asset. More specifically, the presented effort examined the processing of targeting data from an aerial scout vehicle for the purpose of engaging a moving target in a non-line-of-sight engagement. The method and techniques presented are not limited to the specific application and could be easily adapted by similar systems. The solution, however, is not a direct fit for all applications as some work is required to ensure the entities involved align with the described form factor, the specifics of the scenarios need to be determined, and the engagement practices have to be defined. Overall, the presented work is a step towards the proper integration and utilization of new and emerging battle field assets for the purpose of extending/enhancing the capabilities of legacy and developmental weapon systems.

7. REFERENCES

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