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Estimation and Guidance Strategies for Vision-based Target Tracking

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***Abstract*— This paper discusses estimation and guidance strategies for vision-based target tracking. Specific applications include formation control of multiple unmanned aerial vehicles (UAVs) and air-to-air refueling. We assume that no information is communicated between the aircraft, and only passive 2-D vision information is available to maintain formation. To improve the robustness of the estimation process with respect to unknown target aircraft acceleration, the nonlinear estimator (EKF) is augmented with an adaptive neural network (NN). The guidance strategy involves augmenting the inverting solution of nonlinear line-of-sight (LOS) range kinematics with the output of an adaptive NN to compensate for target aircraft LOS velocity. Simulation results are presented that illustrate the various approaches.**

I. INTRODUCTION

As demonstrated in recent events, UAVs are becoming an important component of our military force structure. Looking forward, maintaining a formation while executing missions in the presence of terrain and obstacles is seen as an important challenge. It will also remain important to minimize communication between vehicles. In this paper, we focus on measurement, estimation and formation control guidance strategies [1]-[4].

Although imperfectly understood, flocking behavior of birds, schooling behavior of fish, and even studies of swarming insects have provided inspiration for concepts of coordinated multi-vehicle operation [5]. Existing work on coordinated group motion include a distributed behavioral approach to synthesizing the flocking motion of boids [6] (bird and fish-like objects).

Most of the approaches for formation control assume that a leader vehicle state of motion is known at least partially to the follower (neighboring) vehicles [1]-[3]. The approach taken here is to observe these quantities through passive vision information. That is, a single camera is provided with a view of another aircraft, and that imagery is processed in real-time to determine other aircraft state information. We assume that the image is represented in terms of a noisy measurement of image center and size [7]. The image size measurement is not a viable measurement at large ranges, and in this case we rely on bearing information. This represents a "worst case" for vision-based formation control. We construct an Extended Kalman filter (EKF) to estimate relative velocity and position, which we utilize in the guidance policy [7],[8]. In general, regardless of the approach taken to processing vision-based data, the distance between one vehicle and any other vehicle is difficult to estimate. If we use poor range estimates to control a vehicle performing station-keeping with the target, a dangerous proximity may occur. It is well known that the accuracy of range estimation depends on camera translating motion, and the best translation for range estimation is a motion parallel to its image plane [9].

Another associated problem is the influence of the unknown target aircraft acceleration on the estimates provided by the EKF. The unknown acceleration acts as unmodeled disturbances on the estimation process, giving rise to biased or even diverging estimates. In this paper, we discuss a method to augment an EKF with a neural network (NN) based adaptive element that provides robustness to unknown and unmodeled dynamics. In a complementary approach, the nominal guidance policy associated with regulating the vision measurements is augmented with the output of an adaptive NN that compensates for the effect of target aircraft motion on the dynamics of these measurements.

For the guidance strategies, we assume that the aircraft do not communicate velocity vector information. The lack

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of relative velocity vector information is treated as modeling uncertainty, whose effect on line-of-sight (LOS) range (output) regulation is to be canceled by the output of an online adaptive neural network (NN) [4]. As a result, each vehicle can regulate both the range and relative orientation to a leader and/or neighboring vehicle without knowing the state and control policy of that vehicle. It is assumed that each vehicle can measure or estimate its own speed, heading, range and LOS angle to other vehicles.

Obstacle avoidance is a problem that, in general, cannot be completely separated from that of maintaining a formation, as obstacle avoidance considerations must take precedence. There are numerous approaches to static obstacle avoidance. A popular approach is the Artificial Potential Field Approach [10]. Other approaches include Motion Planning [11] and "Steer Towards Silhouette Edge" [12]. In this paper we describe and implement the latter approach, as in [4].

The organization of the paper is as follows. Section II summarizes the theory for vehicle state estimation. Section III describes the guidance strategy for formation control and describes the approach to avoiding static obstacles. In Section IV we present and discuss simulation results for each approach.

II. BEARINGS-ONLY TARGET STATE ESTIMATION

A. Filter Design

The EKF formulation described in [8] is utilized per other vehicle that requires state estimation. At most, this could include all vehicles in the formation estimating the state of all others. The four states used per filter have the dynamics

$$\frac{d}{dt}\begin{bmatrix} \dot{\beta} \\ \frac{\dot{r}}{r} \\ \beta \\ \frac{1}{r} \end{bmatrix} = \begin{bmatrix} -2\dot{\beta}\frac{\dot{r}}{r} + \frac{1}{r}\left(a_y \cos\beta - a_x \sin\beta\right) \\ \dot{\beta}^2 - \left(\frac{\dot{r}}{r}\right)^2 + \frac{1}{r}\left(a_y \sin\beta + a_x \cos\beta\right) \\ \dot{\beta} \\ -\frac{\dot{r}}{r}\frac{1}{r} \end{bmatrix}. \qquad (1)$$

where β is the bearing to the other aircraft, r is the range, and a_x and a_y are the horizontal relative acceleration components in a Cartesian frame, i.e., the acceleration of the target minus the acceleration of the platform doing the estimation. These components are illustrated in Figure 1, for aircraft i tracking aircraft j.

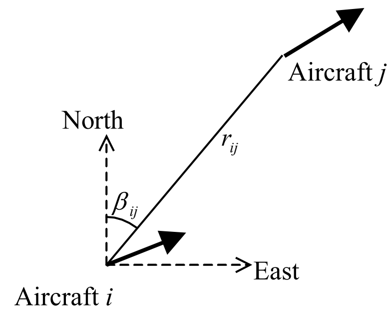

Fig. 1. Illustration of parameters for tracking of aircraft *j* by aircraft *i*.

Here it assumed that each vehicle knows its own heading though typical sensing methods. As a result, the relative bearing information provided by vision sensing another aircraft is immediately converted to a bearing to the other aircraft. The acceleration of the platform doing the estimation is considered known through measurement. This EKF formulation is extended to a three-dimensional case by adding an elevation angle and its changing rate to the measurement and state.

B. Range Observability

Range information is unobservable without certain maneuvers. It is well known that the best relative motion for range estimation accuracy is a motion that is perpendicular to the line-of-sight (LOS) [9]. The optimal maneuver for range estimation is determined by maximizing that "best" motion [13]. For the bearings-only target state estimation, analysis of the contributing factors to the range estimate covariance indicates that a large magnitude of $\dot{\beta}$ gives more accurate range estimation. This also makes sense physically, as viewing the tracked vehicle from a different direction will provide information about position in an additional dimension. From this analysis, it is concluded that $\dot{\beta}$ should be maximized in order to obtain an accurate range estimate. At the same time, it is preferred that the relative bearing stay close to its prescribed desirable value. Also, it is important to limit the acceleration $\ddot{\beta}$. Therefore, an optimization problem that maximizes the predicted range estimation accuracy is formulated as

$$\min_{\ddot{\beta}} \int \{-\dot{\beta}^2 + \frac{K_1}{2}(\beta-\beta_d)^2 + \frac{K_2}{2}\ddot{\beta}^2\} dt$$

subject to the relative motion dynamics (1). The Hamiltonian H and the Euler-Lagrange equations for this optimization problem are formulated as given by (2).

$$
\begin{aligned}
H &= -\dot{\beta}^2 + \frac{K_1}{2}(\beta - \beta_d)^2 + \frac{K_2}{2}\ddot{\beta}^2 + \lambda_1 \dot{\beta} + \lambda_2 \ddot{\beta} \\
\frac{\partial H}{\partial \ddot{\beta}} &= K_2 \ddot{\beta} + \lambda_2 \\
\dot{\lambda}_1 &= -\frac{\partial H}{\partial \beta} = -K_1(\beta - \beta_d) \\
\dot{\lambda}_2 &= -\frac{\partial H}{\partial \dot{\beta}} = 2\dot{\beta} - \lambda_1
\end{aligned} \tag{2}
$$

where λ_1 and λ_2 is Lagrange multipliers. Those equations can be solved analytically and the optimal solution for the bearing angle is derived as follows.

$$
\begin{aligned}
&\beta(t) = A_1 e^{c_1 t} + A_2 e^{c_2 t} + A_3 e^{c_3 t} + A_4 e^{c_4 t} \\
&K_2 c_i^{\,4} + 2 c_i^{\,2} + K_1 = 0
\end{aligned} \tag{3}
$$

Since K_1 and K_2 are positive, all coefficients c_i have a nonzero imaginary value. That is, the optimal relative bearing angle is represented as sine and cosine functions. For example, if we choose K_1 and K_2 which satisfy $K_1 K_2 = 1$, then $\beta(t)$ becomes simply

$$
\beta = A\cos\omega t + B\sin\omega t\,, \quad \omega = \sqrt{K_1} \tag{4}
$$

C. Subtended Angle

In the previous section, we derived the optimal relative maneuver that maximizes the range estimation accuracy. However, it is not desirable that a follower aircraft always needs to make maneuvers during tracking a target aircraft. The alternative strategy to maintain range observability while avoiding a maneuver is to introduce a new measurement of a subtended angle [7]. An image of the target provides indirect observation of the range through measurement of target size in the image plane. The size of the target is defined to be the longest axis of the plane (typically, the wing span). Measuring the angle subtended by the target size in the image plane renders range observable. The EKF is augmented with an additional target size state to utilize the subtended angle measurement.

D. Adaptive Estimation

A method for augmenting a linear time invariant estimator with a NN based adaptive element was described in [14]. This approach has recently been extended to augment an EKF [15]. These approaches provide robustness to unknown and unmodeled dynamics in the process. A critical application of the adaptive EKF lies in the realm of tracking maneuvering targets, particularly in the bearings-only target-tracking problem. It is well known in the target-tracking literature that the accuracy of the resulting EKF estimates depends extensively on the target behavior. The universal approximation property of NNs has paved the way for NN-based identification and estimation schemes that may account for these unknown modeling errors/uncertainties in the process. The training signal for the NN is generated by the residuals produced by the EKF. The residuals are the difference between the image plane measurements and the EKF estimates.

III. Guidance for Formation Flight

The estimates of the range and LOS angle (bearing) from the EKF described above are used in guidance policies for keeping formation. The guidance policies are based on commanding a velocity vector in order to regulate the range and LOS angle to desired values, while avoiding obstacles in the environment [4]. An alternate way of formulating the guidance policy is to not use the estimates from the EKF because of the possibility of biased estimates, but directly regulate the subtended angle and LOS angle to desired values [17]. In the sections below, we discuss the problem formulation for vision-based formation control of multiple UAVs.

A. Problem Formulation

We formulate the problem of vision-based formation control in the framework of NN-based adaptive output feedback control [16]. The range (or, subtended angle) and the LOS angle are treated as outputs available from vision sensors for feedback and control. We assume that the vehicles do not communicate velocity vector information. The lack of relative velocity vector information is treated as modeling uncertainty, whose effect on LOS range (output) regulation is to be canceled by the output of an adaptive NN.

We design an inverting controller augmented with a NN for aircraft i (follower) for regulating the LOS range r_{ij} with respect to aircraft j (leader) [4]. The controller architecture is as shown in Fig 2.

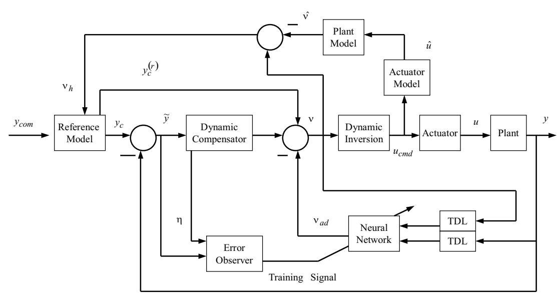

Fig. 2. MRAC architecture for Output Feedback Control and with Pseudo-Control Hedging (PCH).

Aircraft i constructs a pseudo-control signal $\nu_{(i,j)}$ that represents desired LOS range kinematics with respect to the aircraft j. The pseudo-control signal is the sum of signals from a reference model, a dynamic compensator and an adaptive NN as shown in Fig 2. The expression for $\nu_{(i,j)}$ is given below

$$\nu_{(i,j)} = \dot{r}_{c(i,j)} + k_{p_i}\left(r_{c(i,j)} - r_{ij}\right) - \nu_{ad(i,j)} \tag{5}$$

The relative degree of r_{ij} with respect to the speed and heading of aircraft i is 1. Hence the range command R_{com}^{ij}, for the separation between the aircraft i and j, is filtered through a first order reference model. The dynamic compensator is just a proportional error controller in this case. The NN output $\nu_{ad(i,j)}$ compensates for the unknown leader aircraft velocity. The inputs to the NN are the delayed values of the LOS range and angle time histories, and the delayed values of the own aircraft speed and heading time histories.

The pseudo-control signal $\nu_{(i,j)}$ represents the commanded LOS range-rate for aircraft i with respect to aircraft j. The pseudo-control signal is inverted to give a commanded velocity vector $\vec{V}_{FC_i}$ for aircraft i. In case aircraft i is regulating LOS range with respect to multiple neighboring aircraft, say $m > 1$ in number, then the commanded velocity vector for aircraft i is given by the vector sum of the pseudo-control signals oriented along the LOS direction from aircraft i to aircraft j [4],

$$\vec{V}_{FC_i} = -\sum_{j,j\neq i}^{m} \vec{v}_{(i,j)}\,, \tag{6}$$

The velocity vector command that is input to an inner-loop controller. The inner-loop controller generates acceleration commands to achieve the velocity vector command of the formation controller.

B. Static Obstacle Avoidance

The controller design strategy for static obstacle avoidance is based on a reactive "steer towards silhouette edge" approach [12]. The idea is to project the shape of nearby obstacles onto the local, velocity-fixed frame of the vehicle. If this projected shape, adjusted (enlarged) to allow for the size of the vehicle and uncertainty, surrounds the origin of the velocity frame, then some portion of the obstacle is dead ahead (see figure 3). The vehicle must steer away to avoid a collision, and the most efficient direction to turn is toward the portion of the projected shape that is closest to the origin.

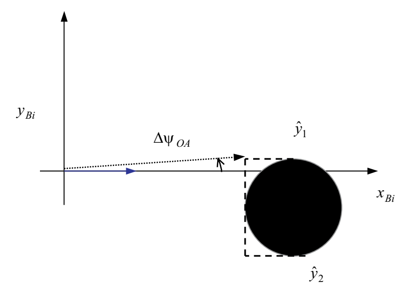

Fig. 3. Illustration of obstacle avoidance approach described here. Lateral acceleration required to miss target is applied once it exceeds a threshold value.

To illustrate the concept, it is assumed that the obstacles are contained within bounding spheres (circles in 2 dimensions), and that the centers X_o, Y_o and radii r_o of the obstacles are known. The goal of this strategy is to keep an imaginary line L_o of length D_o, originating at the vehicle current position and extending in the direction of the velocity vector, from intersecting with any obstacle boundary. The length of this line is typically based upon the vehicle's speed and maneuverability. An obstacle further away than this length D_o is not an immediate threat.

Corrective steering action to avoid an obstacle involves a speed and heading change command. The heading change command $\Delta\psi_{OA}$ is towards the closest projected edge of the obstacle as shown in figure 4. No speed change is used. The corresponding lateral acceleration command can replace the formation flight command when obstacle avoidance is required. When the hazard has passed, the vehicle then returns to the formation.

IV. Simulation Results

Figures 4 and 5 show results obtained with the bearings-only, non-adaptive target state estimation approach. We consider a team of 3 aircraft flying in formation in a 2 dimensional environment in the presence of obstacles. Aircraft #2 is the leader. It sets the trajectory for the formation by commanding a sequence of heading changes while maintaining a constant speed. Each follower aircraft regulates a time-dependent relative position to the leader. In addition, the 3 aircraft are also commanded to avoid obstacles.

The ground track for a typical simulation result is illustrated in figure 4. The leader performs a series of left and right turns, although during one of the turns it must avoid an obstacle instead. The two followers also occasionally must avoid one of the four obstacles. The position estimate for the leader is also shown for each of the two followers. Here, the relative commanded position is held constant, and estimation performance suffers.

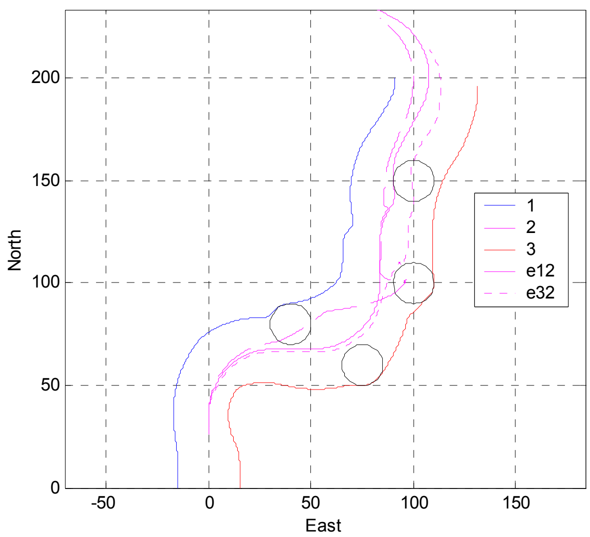

Fig. 4. Ground track of a typical result. The formation starts at the bottom, and proceeds to the top. Aircraft #2 (center) is the leader. The estimated positions for the leader are also plotted for both followers. Both followers and the leader are occasionally required to maneuver to avoid one of the four fixed obstacles. Without utilizing a time-dependent formation shape, range tends to be under-predicted.

A slight periodic time dependency is added for the result in figure 5. The changes in commanded relative position, yields acceptable estimation performance.

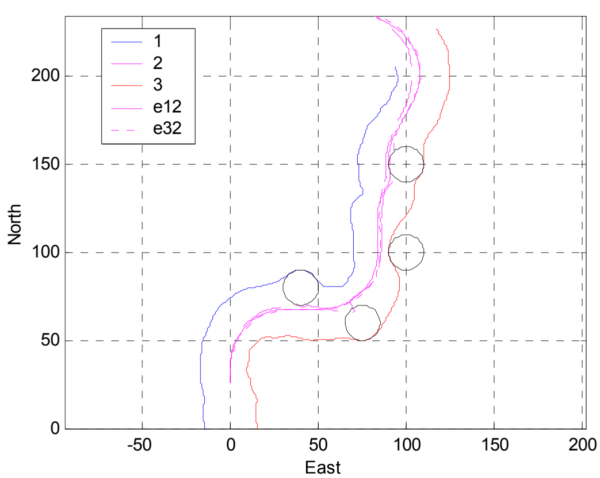

Fig. 5. The formation starts at the bottom, and proceeds to the top. Aircraft #2 (center) is the leader. The estimated positions for the leader are improved by slight periods changes in formation shape.

Figure 6 shows tracking results with a highly maneuvering leader aircraft. Only 1 follower aircraft is included in this simulation. The leader aircraft commands a sinusoidal heading maneuver at constant speed. The upper plot shows the trajectory of the leader, and the follower and an estimate of the leader trajectory by the follower. The bottom plot shows the true range, estimated range by the Follower and the commanded range. The reason for the poor estimates is that the model for the leader acceleration used in the estimation process is highly inaccurate.

Figure 7 show results for the same leader aircraft maneuver obtained by augmenting the EKF with an adaptive NN, where the true and estimated ranges correspond very well, indicating that the NN is able to reconstruct target acceleration.

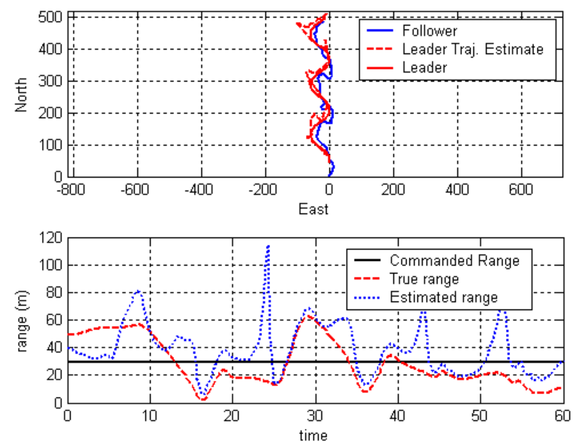

Fig. 6. Range Estimation for a sinusoidally maneuvering leader with *non-adaptive* bearings-only approach. The estimated range varies significantly from the true range because the Leader acceleration is not accurately modeled in the estimation process.

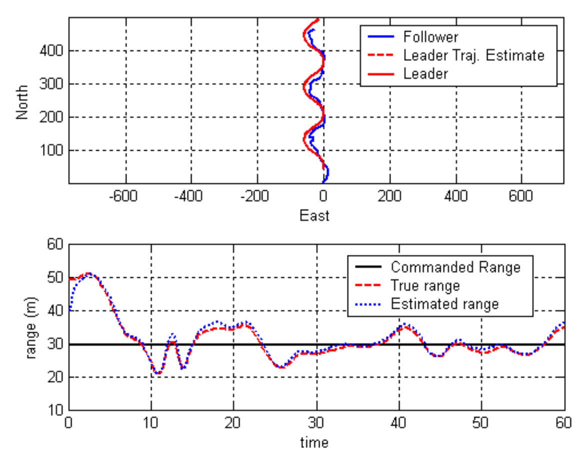

Fig. 7. Range Estimation for a sinusoidally maneuvering leader with *adaptive* bearings-only approach. The range estimation is excellent compared to the non-adaptive bearings only approach, the NN is able to reconstruct target acceleration.

Figure 8 shows the trajectory of a team of 4 aircraft in formation and simultaneously avoiding obstacles. Aircraft 1 is the leader aircraft and the other three are followers. Each aircraft regulates LOS range from each other.

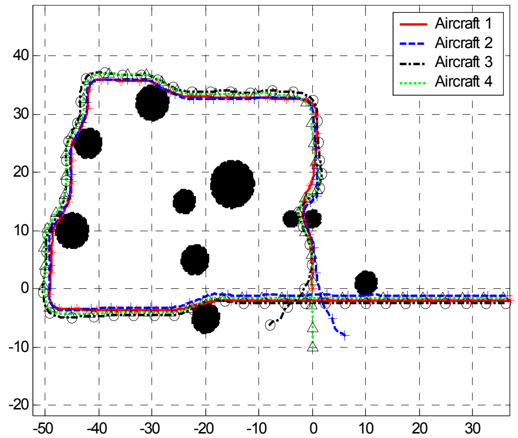

Fig. 8. Multiple Aircraft Formation with Adaptive Guidance Strategy

Fig. 9 shows the errors in commanded range for all pairs of aircraft. Note that the errors go to zero in the steady-state. The range is shown in non-dimensionalized units.

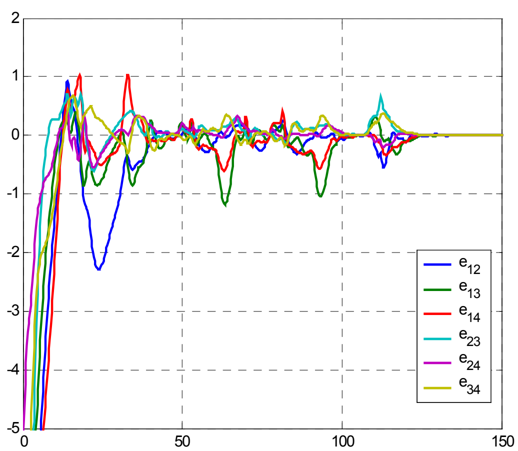

Fig. 9. Commanded Range Errors with Adaptive Guidance Strategy

V. CONCLUSIONS

In this paper, approaches for vision-based estimation and formation control of multiple aircraft are discussed and implemented. No communication is required between vehicles, and simple passive vision processing is assumed, sufficient only to provide noisy bearing and image size measurements. Effects of unmodeled leader aircraft acceleration on the estimation and guidance processes are shown, and adaptive methods to compensate for the same are discussed and demonstrated in simulation.

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