Behaviour Monitoring on Ground Vehicles by UAVs

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Abstract

This paper focuses on developing a behaviour recognition technique for airborne monitoring of moving ground vehicles to detect hidden threats. To enhance tracking accuracy, sensor fusion and smoothing are applied to a Kalman filter tracker. Driving trajectory classification is proposed using differential geometry, and string matching algorithm is applied with handling roadmap information for suspicious behaviour recognition of ground vehicles. Lastly, a standoff tracking guidance law is integrated to continuously chase and closely monitor the recognised suspicious vehicles. Numerical simulations are done to verify the feasibility of the proposed algorithms with a scenario involving multiple UAVs and multiple ground vehicles.

1 Introduction

Using a swarm of UAVs has been receiving attention for a variety of applications to take advantage of its inherent flexibility and versatility. The focus of this study is airborne monitoring of ground traffic behaviour by multiple UAVs in order to detect disguised threats and then to notify the human commander about the potentially dangerous vehicles. A baseline scenario of this study initially deals with detection and identification of a frequently-happening irregular driving behaviour around a military base. For this to be done, the overall autonomy should be able to provide continuity of tracking of the vehicles of interest and thus enable positive identification of suspects. Since typical ground traffic involves interacting motion between several vehicles, achieving the proposed capabilities by a single sensor platform is unlikely to be feasible. Moreover, long endurance surveillance is required, with good spatial coverage, which would be difficult to accomplish with manned aircraft. Therefore this paper investigates a swarm of airborne sensor platforms endowed with an appropriate level of autonomous decision making to support the human commander.

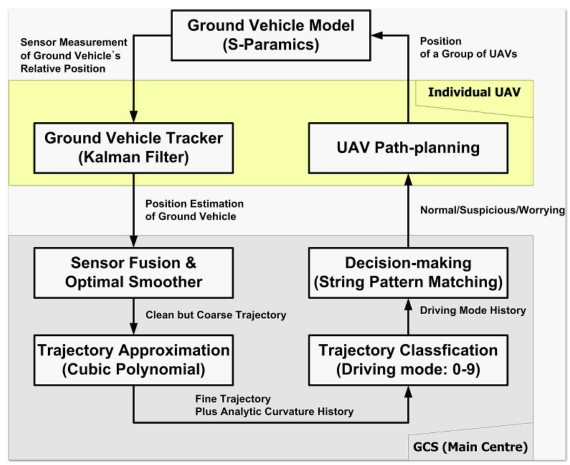


Figure 1: An overall flowchart for decision-making

To satisfy the requirements aforementioned, this paper accommodates the tracking filter design for ground vehicles, sensor fusion, trajectory classification and recognition based on differential geometric quantities and symbolic dynamics. In addition to these, a coordinated standoff tracking guidance law is applied so that multiple UAVs keep track of the recognised suspicious ground vehicle. The position estimation accuracy of the ground vehicle is enhanced by the sensor fusion based on track-to-track fusion and optimal smoothing. Then, a novel trajectory classification methodology is proposed using differential geometrical quantities of the ground target that can be obtained from the abovementioned tracking filter and sensor fusion techniques. This is the most important part of this study since the quantitative value of the motion characteristics of the ground vehicle needs to be simplified as the irregular driving behaviours take place for not a single sampling time, but a longer length of time. Through this simplification of the target characteristics, then the string matching algorithm can be applied to identify the irregular driving behaviour. Lastly, this paper performs numerical simulations using an artificial environment around a military base in order to verify integration and feasibility of the proposed methodology. A overall flowchart of this study is shown in Fig. 1.

2 Tracking filter and sensor fusion

2.1 Target modelling

Kalman-filter-based tracking has traditionally been developed for monitoring aerial targets: aeroplanes, missiles etc. However, ground vehicles basically move with lower speeds than aerial targets and irregularly perform stop-and-go manoeuvres with much smaller turn radius than aircraft. A constant velocity model broadly used for radar target tracking seems thus unsuitable for tracking of ground traffic, and hence an acceleration or a jerk model may be a candidate instead. After analyzing the car trajectory data of S-Paramics[1] traffic simulation program, it can be seen the jerk is not negligible, but the acceleration is piecewise constant for a specific length of time. In this study, therefore, a discrete Kalman filter considering the acceleration dynamics [1] is applied to tracking of the ground vehicle. Discretised system/measurement equations and process noise covariance matrix can be found in our previous publications [2, 3].

2.2 Sensor modelling

This study assumes the UAV are equipped with a MTIR (Moving Target Indicator Radar) to localise the position of target. Because the measurement of MTIR is composed of range and azimuth of the target with respect to the radar location, the actual measurements is the relative range and azimuth with respect to the position of the UAV airborne. The radar measurement $(r, \phi)^T$ can be defined as a non-linear relation using the target position $(x_k^t, y_k^t)^T$ and the UAV position $(x_k, y_k)^T$, which can be found in [4].

2.3 Extended Kalman tracker

Considering the measurement equation is nonlinear, the localisation of target can be designed using an EKF (Extend Kalman Filter) [5] as can be found in [4].

[1] http://www.sias.com

2.4 Multi-sensor fusion

Since this study assumes a pair of UAVs carry out the cooperative standoff tracking of a ground moving target, each UAV's MTIR sensor can get its own measurement and execute the tracking filter algorithm separately. After each UAV receives the other's estimation via communication link, it can run a decentralised sensor fusion to enhance the tracking accuracy. This study simply adopts the following state-vector fusion also known as a track-to-track fusion [6, 4] under the assumption that the communication bandwidth is wide enough to transmit the state (6-by-1) and covariance matrix (6-by-6) in both directions between a pair of UAVs.

$$\hat{\mathbf{x}}_k^t = \mathbf{x}_{k|k}^t + P_{k|k}(P_{k|k} + P_{k|k}^p)^{-1}(\mathbf{x}_{k|k}^{tp} - \mathbf{x}_{k|k}^t) \quad (1)$$
$$P_k = P_{k|k} + P_{k|k}(P_{k|k} + P_{k|k}^p)^{-1}P_{k|k}^T \quad (2)$$

where $\mathbf{x}_{k|k}^{tp}$ and $P_{k|k}^p$ represent the state and error covariance estimations of the pair UAV. Instead of the state-vector fusion, the fusion using information filter [7] can be used for minimising the communication load.

2.5 Optimal smoother

As the behaviour of ground vehicle will be analysed with a moving horizon history, accuracy of past state estimates can be improved by using an optimal fixed-interval smoother [5]. Generally the optimal smoothing algorithm is composed of a forward filter and a backward filter. The basic idea of the optimal smoothing is that if the measurements between t and $T_f(> t)$ are available, the estimates of the forward filter at time t, $\hat{x}_f(t)$, can be adjusted based on the estimates of the backward filter at that time, $\hat{x}_b(t)$. The detail derivation of the optimal smoother can be found in [5]. The forward filter generally adopts the Kalman filter already described in the previous section. The detailed algorithm can be found in [2, 3].

3 Classification of driving behaviour

To recognise a driver's irregular behaviours, it is necessary to classify the moving-window trajectory acquired in the previous section. The driving manoeuvre does not happen for a single sampling time, rather it happens for a specific length of time. For instance, let us suppose an aggressive driver is repeatedly weaving, i.e. changing lanes with a short interval. To detect that, we have to store that vehicle's trajectory classification history, i.e.

driving mode, and then must perform decision-making on whether the vehicle performs worrying behaviour and what type of behaviour that is. Since the design of the tracking filter, sensor fusion, and smoothing was already done in the previous section, let us move on to the trajectory classification involving how to sort out driving behaviours. Based on Fraile and Maybank [8] and Oliver and Pentland [9], we proposed a new driving-mode classification composed of nine driving modes [2, 3]. Figure 2 shows a full flowchart of the car trajectory classification.

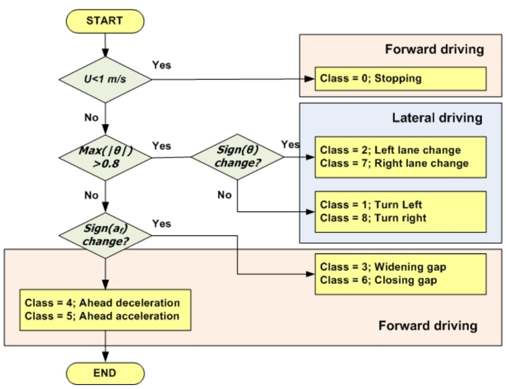


Figure 2: A flowchart of trajectory classification

4 Behaviour recognition

4.1 Approximate string matching

The essence of the classification was to categorise characteristic manoeuvres associated with forward or lateral driving by assigning them to one of nine classes: $\{0, \ldots, 8\}$, as dealt with in the previous section. This allows not only to recognise characteristic fragments of the trajectories, but to enable recognition of ground traffic behaviour in a theoretically sound, intuitive, robust, computationally-efficient and flexible way. A key tool for this detection scheme is string matching which is a well-developed area of text processing. String matching consists in finding all the occurrences of a string (called a pattern) in a text. In this study, using the alphabet $\{0, \ldots, 8\}$, a symbolic time series y_i is generated for each $i = 1, \ldots, N$ using a N sampling time trajectory by target-tracking and classification. However, to find the exact string matching to a certain behaviour class is not technically easy and computationally burdensome. In this case, we need to define a cost measuring the distance or the similarity between the reference patterns and the test patterns, as which this study adopts a concept of Edit distance. The Edit distance between two patterns is defined as the cost to convert one pattern to the other. If the patterns are of the same length, then the cost is directly related to the number of symbols that have to be changed in one of them so the other pattern results. In case the two patterns are not of equal length, symbols have to be either deleted or inserted at certain places of the test string [10]. Although this problems arises in automatic editing and text retrieval applications, it is worth considering for detection of driving mode sequences similar but not exactly matching to the predefined interested sequences. The details of the approximate string matching can be found in our previous works [2, 3].

4.2 Use of roadmap information

To effectively tackle behaviour recognition, a time history of environmental information as well as the driving mode profile is required, which could be a relative position of the suspicious ground vehicle to the critical area, e.g. the centre of complex activities and the base walls or an index of road that the ground vehicle has moved along. Assuming that the local roadmap information is readily available to the military operator, the indexes of the local roads near the military base can be annotated by a sequence of numbers. Figure 4 shows the road index numbers of the scenario roadmap considered in this study. Another important information for the local roadmap is the properties of junctions. In Fig. 4, for instance, a vehicle driving to the north on the road index 1 has two choices: keeping to the north on the road index 2 or turning right to the east on the road index 5. On the other hand, a vehicle driving to the west on the road index 7 has only a choice: turning right to the north on the road index 8. Therefore if the shape of roadmap and the junction characteristics are available, the time history of the road index on which the vehicle is moving can be easily obtained. In this simulation, the road index history is decided using the information on the positions of junctions and the driving direction after passing over each junction.

5 UAV guidance for standoff tracking

Assuming each UAV has a low-level flight controller for heading and velocity hold functions, this section aims to design the guidance inputs to this low-level controller for cooperative standoff tracking. The guidance command is $\mathbf{u} = (u_v, u_\omega)^T$: commanded speed and turning rate constrained by $|u_v - v_0| \leq v_{max}$ and $|u_\omega| \leq \omega_{max}$ where v_0 is a nominal speed of UAV. The details of UAV kinematics model can be found in [4].

SHBG (Supercritical Hopf Bifurcation Guidance)
Let us consider the following Lyapunov candidate function: $V(x,y) = (r^2 - r_d^2)^2$ where $r = \sqrt{\delta x^2 + \delta y^2} = \sqrt{(x-x_t)^2 + (y-y_t)^2}$ is the distance of the UAV from the ground vehicle. Herein (x_t, y_t) is the position of the ground vehicle which can be estimated from the tracking filter, and r_d is a desired standoff distance from the UAV to the ground vehicle. The geometry between the UAV and the ground target is shown in Fig. 3. Let us consider

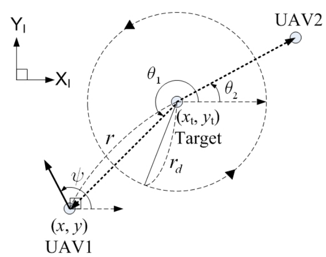


Figure 3: The geometry between UAV and ground target

the following desired velocity $[\dot{x}_d, \dot{y}_d]^T$ [11]:

$$\begin{bmatrix} \dot{x}_d \\ \dot{y}_d \end{bmatrix} = \begin{bmatrix} -\delta y + \frac{\delta x}{k r_d^2}(r_d^2 - \delta x^2 - \delta y^2) \\ \delta x + \frac{\delta y}{k r_d^2}(r_d^2 - \delta x^2 - \delta y^2) \end{bmatrix} \tag{3}$$

where k is a positive constant. Substituting Eq. (3) into the time derivative of the Lyapunov candidate function yields $\dot{V}(x,y) = -\frac{4r(r^2-r_d^2)^2}{kr_d^2} = -\frac{4r}{kr_d^2}V$. Herein, $\dot{V} \leq 0$ except $r = 0$, and then r converges to the largest invariant set $r = r_d$ satisfying $\dot{V} = 0$ by LaSalle's invariance principle. The desired heading can be decided using the desired two dimensional velocity components in Eq. (3) as: $\psi_d = \tan^{-1}\frac{\dot{y}_d}{\dot{x}_d}$. The guidance command u_ψ for turn rate is selected as the sum of proportional feedback and feedforward terms as: $u_\psi = -k_\psi(\psi - \psi_d) + \dot{\psi}_d$.

In the meantime, to maximise sensor coverage to the target and prevent collision, the phase coordination between the UAVs is required during the mission. This study adopts a phase-angle keeping guidance law to change the speed of UAVs as proposed in [12].

6 Simulation result

6.1 Assumptions and conditions

Figure 4 shows the scenario description in which two ground vehicles are moving around a military base to be monitored by two UAVs. In the map, at the southern area of a river, there is a military base of strategical importance to be protected, which has a surrounding roadmap to be passed by a civilian ground vehicle near the base wall. Crossing the river on the bridge, a local bazaar place is located at the northern area of the river which is regarded as a centre of complex activities to be monitored for security reasons in this study. The interested suspicious behaviour of a ground vehicle is: H1 (passing through a centre of complex activities), H2 (subsequently turning around to repeat its route), and stopping near base walls (H3).

Car 1 circles clockwise round the military base twice. During that time, the vehicle stops for 10 seconds on the mid of Road 3 near 425s. After that, it crosses on the bridge and then passes into the local bazaar area at 867s, and finishes its journey. Meanwhile, Car 2 departs from near the right-lower corner of the military base and goes straight to the North crossing the bridge during 89s. After turning left, the vehicle stops for 10s and penetrates the local bazaar at 150s. Then, it turns to the south and comes back to the departing location.

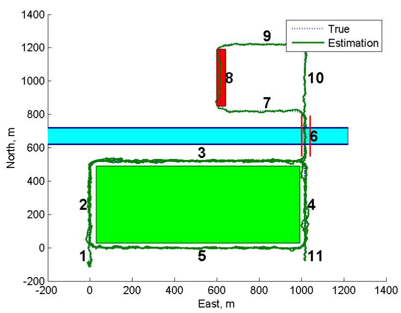
The true MTIR measurements of a pair of UAVs were mixed with the white noise having the following standard deviations: $(\sigma_{r1}, \sigma_{\phi 1}) = (5.0m, 3.5deg)$,$(\sigma_{r2}, \sigma_{\phi 2}) = (7.5m, 2.0deg)$

6.2 Simulation results

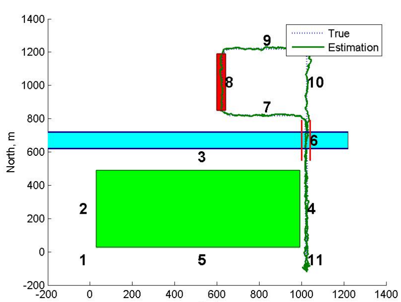
Firstly, EKF and decentralised sensor fusion with state-vector fusion shows a reasonable tracking accuracy on two ground vehicles as shown in Fig. 4-5. The trajectory classification histories of two ground vehicles are drawn in Fig. 6. Meanwhile, the road index histories on which two cars are moving are presented in Fig. 7. The histories of Figs. 6-7 lets UAVs know Car 2 suspiciously stops by the local bazaar (road number: 8) at 149 seconds, and at the same time, this is declared in Fig. 8(b). From that time, two UAVs start tracking against Car 2 with keeping a standoff distance and a phase angle between them.

At 315 seconds, Car 1 repeats its route around the military base, which can be monitored by the roadmap index history as shown in Fig. 7, which is declared in Fig. 8(a). Then, one of two UAVs tracking Car 2 together is separated from the formation and begin to fly to the standoff circle of Car 1. After that, each UAV has to track and carry out surveillance separately. After the first detection of route retrieval, irregular behaviours with stopping and additional circling around the base wall are detected and declared in Figs. 6-8.

Figure 9 displays the absolute trajectories of UAVs and ground vehicles and the relative trajectories of UAVs with respect to the positions of the ground vehicles. As can be seen in Figs. 9(b)-10(a), the standoff tracking is accurately performed by the SHBG. Figure 10(b) shows that two UAVs keeps well the phase angle as 180 degrees during cooperative tracking against Car 2. In summary, the overall integration of the algorithms was seamlessly done for a military-point-of-view scenario, and finally verifies the performance of the methodologies developed in this study which overarches filtering, sensor fusion, trajectory analysis, string matching, and cooperative guidance.

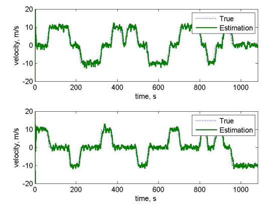


(a) Car 1

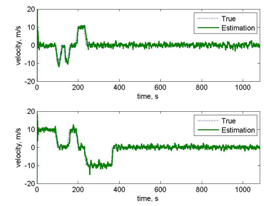


(b) Car 2

Figure 4: Trajectory estimations of ground vehicles

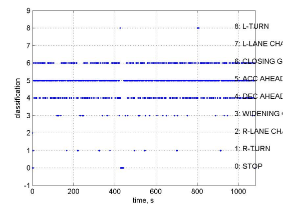


(a) Car 1

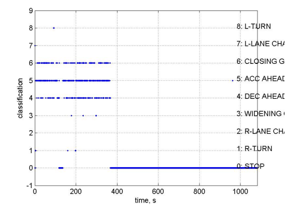


(b) Car 2

Figure 5: Velocity estimations of ground vehicles

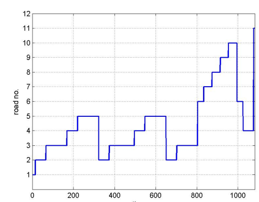


(a) Car 1

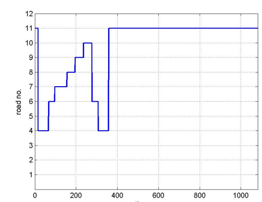


(b) Car 2

Figure 6: Trajectory classification of ground vehicles

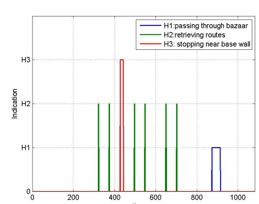


(a) Car 1

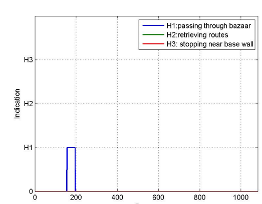


(b) Car 2

Figure 7: Road index history of ground vehicles

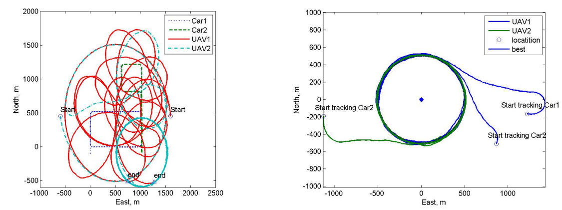


(a) Car 1



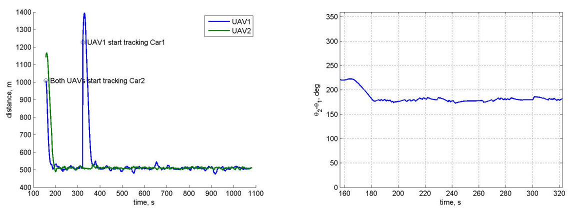
(b) Car 2

Figure 8: Behaviour detection of ground vehicles



(a) absolute trajectories (b) relative trajectories

Figure 9: Trajectories of UAVs and ground vehicles



(a) Standoff distance (b) Phase difference w.r.t. Car 2

Figure 10: Standoff distance from UAVs to vehicles

7 Conclusions

This paper presented a novel approach to airborne monitoring of ground vehicle behaviours by multiple UAVs which integrates various techniques: Kalman tracker, sensor fusion, smoothing, trajectory classification, string matching, and standoff tracking guidance. The proposed approach could be applied to various anomalous behaviour scenarios in view of both military and civil applications.

Acknowledgement

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