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Fuzzy Expert Rule-Based Airborne Monitoring of Ground Vehicle Behaviour

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***Abstract*—This paper proposes an airborne monitoring methodology of ground vehicle behaviour based on a fuzzy logic to identify suspicious or abnormal behaviour reducing the workload of human analysts. With the target information acquired by unmanned aerial vehicles, ground vehicle behaviour is firstly classified into representative driving modes and then a string pattern matching theory is applied to detect pre-defined suspicious behaviours. Furthermore, to systematically exploit all available information from a complex environment and confirm the characteristic of behaviour, a fuzzy rule-based decision making is developed considering spatiotemporal environment factors as well as behaviour itself. To verify the feasibility and benefits of the proposed approach, numerical simulations on moving ground vehicles are performed using both synthetic and realistic car trajectory data.**

***Index Terms*—Airborne monitoring, Target tracking, Trajectory classification, Behaviour recognition, Fuzzy decision making**

I. Introduction

Recently, autonomous airborne surveillance and reconnaissance systems become a challenging and emerging problem in the area of aerospace and robotics with the rapid improvement of the UAV (unmanned aerial vehicle) operation and sensing technology. Airborne monitoring allows suspicious or unusual behaviour to be identified and investigated promptly so that situational awareness can be increased in support of border patrol, law enforcement and protecting infrastructure. For this, many researchers have investigated a swarm of autonomous airborne sensor platforms having a long endurance as well as good spatial coverage with an appropriate level of decision making. In particular, surveillance by UAVs equipped with a MTIR (Moving Target Indicator Radar) sensor can provide a certain level of accurate estimation of a large number of moving targets as well as capability to respond possible threats from the air. However, for detection of suspicious behaviours, the operators have to manually analyse the gathered mass data and construct a coherent picture of events. With these backgrounds, this paper focuses on the development of a high-level analysis algorithm to process target information acquired by UAVs which provide awareness of abnormal behaviour.

In general, detecting anomalous behaviour can be classified into two categories: The first approach codifies the behaviours using experience and domain knowledge of experts and the behaviours are learned from data in the second approach [1]. Purely learning based approaches can provide a good performance [2], [3], however, they require massive data set in advance or tend to suffer from the high computation burden for real-time applications. On the other hand, there are several algorithms to deal with behaviour or activity analysis in the context of codified (or classified) behaviour model with the aid of learning. Srivastava *et. al.* [4] introduced the method to detect anomalies of the ground vehicle by observing the patterns in its velocity called as velocity trajectory using hypothetical co-ordinated system in which the axes are specified with respect to the road segment. Besides, Fraile and Maybank [5] proposed the idea of dividing the trajectories of the ground vehicle into several driving modes using video images which can be exploited for ground traffic surveillance. However, this classification is limited to car manoeuvres in an urban parking space with slow speed. Similarly, Kim *et. al.* [6], [7] proposed the trajectory classification codified with more detailed driving modes, and applied it to string matching theory to detect suspicious behaviour defined from expert knowledge.

This paper proposes a fuzzy expert rule-based airborne monitoring methodology of ground vehicle behaviour as an extension of our previous works mentioned above [6], [7]. In those works, a primary source for the behaviour recognition is a single deterministic cost obtained from the string matching. Although this cost can provide the measure of suspiciousness computing similarity between pre-defined suspicious strings and driving mode history from trajectory classification within a certain time window, additional information needs to be considered to finally confirm the characteristic of behaviour while avoiding frequent false alarms. Therefore, in this study, to systematically exploit all available information interconnected and influenced by each other obtained from complex environment, a fuzzy system is applied considering its ability to classify complex sources into simple and intuitive form resulting in the final decision with some degree of confidence through expert rules. The proposed fuzzy expert rule-based decision making allows to concurrently accommodate several aspects of behaviour as well as spatiotemporal environment factors providing a level of alert to operator monitoring complex scenes.

The overall structure of this paper is given as: Section

II briefly introduces a target tracking filter, trajectory classification, and behaviour recognition algorithm using string matching. Section III introduces rule-based decision making algorithm to find suspicious behaviour based on a fuzzy logic. Section IV presents numerical simulation results of behaviour monitoring for both synthetic and civilian traffic scenario using realistic ground vehicle trajectory data. Lastly, conclusions and future works are addressed in Section V. An overall flow chart the technique presented in this paper is shown in Fig. 1.

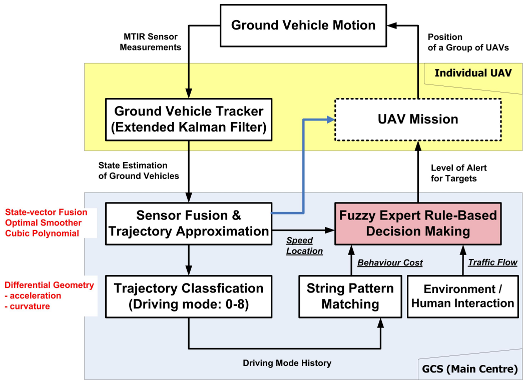


Fig. 1. An overall flow chart of fuzzy expert rule-based behaviour monitoring

II. Behaviour Modelling and Recoginition

This section briefly introduces our previous works on airborne monitoring of ground vehicle behaviour based on [6], [7]. Ground target tracking filter using UAVs is firstly explained. Trajectory classification is followed to model the behaviour of ground vehicles, and lastly behaviour recognition algorithm using string matching theory is presented.

A. Target tracking

This study considers acceleration dynamics to apply it to tracking of the moving ground vehicle. This model regards the target acceleration as a process correlated and exponentially decreasing in time, which means if there is a certain acceleration rate at a time t, then it is likely to be the same jerk also at a time instant $t+\tau$ as:

$$\mathbf{x}_k^t = F_k \mathbf{x}_{k-1}^t + \eta_k \tag{1}$$

where $\mathbf{x}_k^t = (x_k^t, \dot{x}_k^t, \ddot{x}_k^t, y_k^t, \dot{y}_k^t, \ddot{y}_k^t)^T$, η_k is a process noise which represents the acceleration characteristics of the target, and the state transition matrix F_k can be represented as:

$$F_k = \begin{bmatrix} 1 & T_s & \Phi & 0 & 0 & 0 \\ 0 & 1 & \frac{(1-e^{-\alpha T_s})}{\alpha} & 0 & 0 & 0 \\ 0 & 0 & e^{-\alpha T_s} & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & T_s & \Phi \\ 0 & 0 & 0 & 0 & 1 & \frac{(1-e^{-\alpha T_s})}{\alpha} \\ 0 & 0 & 0 & 0 & 0 & e^{-\alpha T_s} \end{bmatrix} \tag{2}$$

where $\Phi = (e^{-\alpha T_s} + \alpha T_s - 1)/\alpha^2$, and α is a correlation parameter which allows for the modelling of the different classes of targets. The details of the covariance matrix Q_k of the process noise η_k can be found in [8].

Besides, this study assumes the UAV are equipped with a MTIR 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 are the relative range and azimuth with respect to the position of the UAV airborne. The radar measurement $(r,\phi)^T$ can be defined as the following nonlinear relation using the target position $(x_k^t, y_k^t)^T$ and the UAV position $(x_k, y_k)^T$ as:

$$\begin{aligned} \mathbf{z}_k &= \begin{pmatrix} r_k \\ \phi_k \end{pmatrix} = h(\mathbf{x}_k^t) + \nu_k \\ &= \begin{pmatrix} \sqrt{(x_k^t - x_k)^2 + (y_k^t - y_k)^2} \\ \tan^{-1} \frac{y_k^t - y_k}{x_k^t - x_k} \end{pmatrix} + \nu_k \end{aligned} \tag{3}$$

where ν_k is a measurement noise vector, and its noise covariance matrix is defined as:

$$V[\nu_k] = R_k = \begin{bmatrix} \sigma_r^2 & 0 \\ 0 & \sigma_\phi^2 \end{bmatrix}. \tag{4}$$

Considering that the measurement equation is nonlinear, the localisation of target is designed using the EKF (Extended Kalman filter). In addition, assuming a pair of UAVs track the same targets, sensor fusion technique using a Covariance Intersection algorithm is applied. Lastly, as the behaviour of ground vehicle will be analysed with a moving horizon history, the optimal fixed-interval smoother is used to improve the accuracy of past state estimation of the target. The details for sensor fusion and optimal smoother can be found in [6].

B. Trajectory classification

To model a driver's behaviour, the trajectory is classified into driving modes. The purpose of the classification is to categorise characteristics of manoeuvres associated with forward or lateral driving by assigning them to driving modes as will be explained in the following. This allows not only to recognise characteristic fragments of the trajectories, but also to enable recognition of ground traffic behaviour in an intuitive, computationally-efficient and flexible way.

Since the driving manoeuvre does not happen for a single sampling time, the trajectories for a certain length of time need to be considered. For this, a moving-window-based trajectory approximation [6] is applied using a polynomial function which generates trajectory with a virtually increased sampling time for a certain time interval. Let us assume a new time sequence within a moving window, $0 < T_n < 2T_n < \ldots < (N_T-1)cT_n = (N_T-1)T_s$ where T_s is an original sampling time of tracking filter, T_n is a new virtual sampling time, and N_T is the number of samplings for a moving window. In this study, it is assumed that $N_T = 4$, $T_s = 0.5$, and $c = 5$, and thus the new virtual sampling time is 0.1 seconds. The selection of $N_T = 4$, i.e. 1.5 seconds' moving window reflects that the bandwidth for lane changing is at least 1.0Hz according to the reference [9]. Then, velocity $(\dot{x}^t(i), \dot{y}^t(i))$ and acceleration $(\ddot{x}^t(i), \ddot{y}^t(i))$ histories with a new time sequence are used to compute the minimum speed U, the rate change of orientation $\theta(i)$, and forward acceleration $a_f(i)$ of the vehicle at current time step k for each i in a moving window (i.e. $k-c(N-1)+1 \leq i \leq k$) as:

$$U = \min v(i) = \min \sqrt{\dot{x}^t(i)^2 + \dot{y}^t(i)^2} \quad (5)$$

$$\begin{aligned}\theta(i) &= v(i)\kappa(i) \\ &= \sqrt{\dot{x}^t(i)^2 + \dot{y}^t(i)^2}\frac{\dot{x}^t(i)\ddot{y}^t(i) - \dot{y}^t(i)\ddot{x}^t(i)}{(\dot{x}^t(i)^2 + \dot{y}^t(i)^2)^{3/2}} \quad (6)\end{aligned}$$

$$a_f(i) = \ddot{x}^t(i)\cos\psi(i) + \ddot{y}^t(i)\sin\psi(i) \quad (7)$$

where κ is a curvature, and $\psi = \tan^{-1}(\dot{x}^t/\dot{y}^t)$ is the heading angle from the North. Using above equations, a driving mode m_k^d among driving mode set $M^d = \{0, \cdots, 8\}$ at time step k can be obtained for each moving window with a frequency of $1/T_s$ as:

- **Stopping (0)**, $U < 1$: Since 1 m/s equals to 3.6 km/h, it can be assumed that the car does not move or is about to stop or start moving.
- **Left turn (1)**, $\max(\theta)\min(\theta) > 0$ and $\max(\theta) > \theta_{th}$: The inspection of sign change of θ is used to distinguish the pure turning maneuver from the lane changing.
- **Right turn (8)** $\max(\theta)\min(\theta) > 0$ and $\max(\theta) < -\theta_{th}$
- **Left lane change (2)** $\max(\theta)\min(\theta) < 0$, $\max(|\theta|) > \theta_{th}$, and $\theta(0) > 0$: The difference to the left turn of this condition is the sign change of the rate of orientation change. The sign of curvature transits from positive to negative in case of the left lane change.
- **Right lane change (7)** $\max(\theta)\min(\theta) < 0$, $\max(|\theta|) > \theta_{th}$, and $\theta(0) < 0$: The sign of curvature transits from negative to positive in case of the right lane change.
- **Closing gap (6)** $\max(a_f)\min(a_f) < 0$, and $a_f(0) > 0$: When the driver wants to close gap to the preceding vehicle, the sign of acceleration transits from positive to negative.
- **Widening gap (3)** $\max(a_f)\min(a_f) < 0$, and $a_f(0) \leq 0$: Contrary to the case of closing gap, the sign of acceleration transits from negative to positive.
- **Accelerating ahead (5)** $\max(a_f)\min(a_f) > 0$, and $a_f(0) > 0$: The sign of acceleration keeps positive.
- **Decelerating ahead (4)** $\max(a_f)\min(a_f) > 0$, and $a_f(0) \leq 0$: The sign of acceleration keeps negative contrary to the case of the accelerating ahead.

C. Behaviour detection

This section introduces behaviour detection scheme to find suspicious behaviour using driving mode histories of ground vehicles. The key tools for this detection scheme are symbolic dynamics and string matching. The mathematical subject of symbolic dynamics originally arose in the theory of dynamical systems and was motivated by the qualitative approach to dynamics in which the character of trajectories is more important than their numerical values. String matching theory 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 where the pattern is a string x of length m, while the text is a string y of length n. In this study, using the driving mode set $M^d = \{0, \cdots, 8\}$, a symbolic time series of driving modes $y_k^d = \{m_l^d \in M^d | l = 1, \ldots, N_{sm}\}$ is generated by trajectory classification for each time step k, where N_{sm} represents a moving window length for string matching. The suspicious behaviour is also expressed as strings x_s consisting of nine numbers.

Intuitive string matching method we can apply is the exact matching which detects exactly the same pattern in the driving mode history as the pre-defined suspicious string. However, assuming a reference suspicious string of '145048', '145548' or '145448' cannot be ignored as well in the detection scheme, whose fourth element of the string might be one of the following forward driving modes: '3'; '4', '5', '6', instead of '0'. To tackle this, an approximate matching is applied by defining a cost which is called as Edit distance measuring distance or similarity between reference and test patterns. The Edit distance $D(S_1, S_2)$ [10] between two string patterns S_1 and S_2 is defined as the minimum number of editions including changes C, insertions I, and deletions R required to change pattern S_1 into S_2. The details of approximate string matching can be found in [6].

Although above edit distance can provide the measure of suspiciousness computing similarity between pre-defined suspicious strings and current driving mode history within a certain time window, additional information needs to be considered to finally confirm characteristic of behaviour while avoiding frequent false alarms. From the following section, what types of information can be used and how to combine them will be dealt with.

III. Fuzzy Expert Rule-Based Decision Making

For airborne behaviour monitoring, this section proposes a decision making algorithm to find suspicious or anomalous vehicle based on a fuzzy logic. To systematically exploit all available information interconnected and influenced by each other obtained from complex environment, fuzzy system is applied considering its ability to classify complex sources into simple and intuitive form (fuzzification) resulting in the final decision (defuzzification) with some degree of confidence (rather than single certain decision) through expert rules (fuzzy inference). The proposed fuzzy expert rule-based decision making allows to concurrently accommodate several aspects of behaviour as well as spatiotemporal environment factors with supervision of human providing a level of alert to operator monitoring complex scene. Fuzzy system used in this study consists of four fuzzy membership functions for inputs and one output with 36 expert inference rules.

A. Fuzzification

A fuzzy input for behaviour monitoring includes four aspects: location, behaviour cost, speed of the vehicle, and environmental aspect as:

- **Location:** A time history of the location which is a relative position of the suspicious ground vehicle to the critical area (e.g. the centre of complex activities and the base walls of military facilities) or an index of road that the ground vehicle has moved along is an important source for behaviour monitoring. Assuming that the local roadmap information is readily available in advance, the indexes of the local roads in region of interest can be annotated by a sequence of road numbers. If the vehicle travelling on one of identified roads of interest, the location is categorised as 'Region of interest (R)'; otherwise is 'General (G)' as shown in Fig. 2(a).

- **Behaviour cost:** As a key factor for the behaviour monitoring, the edit distance D is used resulting in time history of a behaviour cost. Let $X_s = \{x_s^1, \cdots, x_s^{N_{su}}\}$ be the set of pre-defined suspicious behaviours. Then, the behaviour cost C_k^b with respect to current time series of driving modes y_k^d and suspicious behaviours at time step k can be defined as:

$$C_k^b = \frac{1}{\min_{i \in X_s} D\left(x_S^i, y_k^d\right) + 1} \tag{8}$$

  Three fuzzy membership functions with linguistic variable 'Normal (N)', 'Suspicious (Su)', and 'Worrying (W)' are used to categorise the behaviour cost as shown in Fig. 2(b).
- **Speed:** The velocity profile of the vehicle with respect to its position or time step also needs to be investigated since it can provide the measures of the suspicious or abnormal behaviour inherently. Three functions with 'Slow (Sl)', 'Moderate (M)', and 'Fast (F)' are used as shown in Fig. 2(c).
- **Environment:** The last input considers an environmental condition with a human interaction for the behaviour decision process. Depending on the traffic flow density, two functions with 'Normal traffic (Nt)' and 'Congestion (C)' are used as membership functions as shown in Fig. 2(d). Even though only traffic flow is used in this study, it can be easily replaced with time zone such as day/night or weekday/weekend or any other environmental aspects. This input allows for incorporating human supervision on a certain environment into decision making instead of relying only fully autonomous decision process which can be vulnerable to unexpected and dynamic environments.

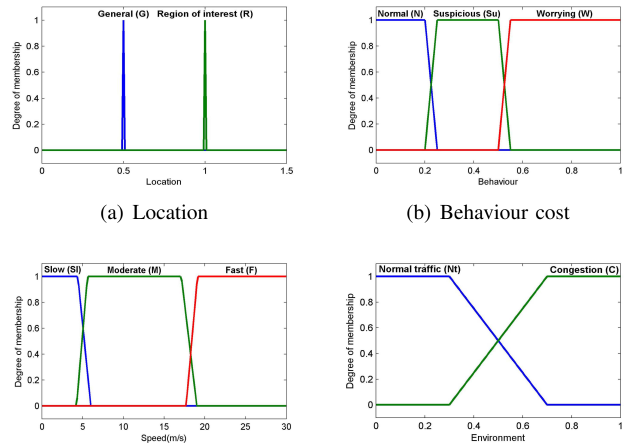
A fuzzy output for behaviour monitoring is the level of alert of each ground vehicle consisting of four membership functions with linguistic variable 'Allow', 'Monitor', 'Investigate', and 'Respond' as shown in Fig. 3.

B. Fuzzy inference

In this study, a fuzzy inference system is designed by using a Mamdani model [11]. Inhere, expert knowledge can be expressed in a natural way using linguistic variables defined above as Table. I∼II. In the table, rules can be interpreted as:

- Rule 1: If Location is 'G' and Behaviour is 'N' and Speed is 'Sl' and Environment is 'Nt', then Alert is 'Allow'.

Note that depending on the location and environment, rules are changed slightly. For instance, if location of the vehicle is 'G' (i.e. general area), speed 'Sl' does not mean something significant leading to alert 'Allow', whereas if the location is 'R' (i.e. region of interest), slow speed or stopping of the vehicle can be identified as suspicious one (monitoring the specific facility or placing of improvised explosive devices) leading to alert 'Investigate' as Rule 1 and 19. However, even though the location is 'R' and speed is 'Sl', if the environment is 'C' (i.e. congestion), its alert level should be alleviated as Rule 20 since slow speed is more likely to be observed.



(a) Location (b) Behaviour cost (c) Speed (d) Environment (Traffic flow)

Fig. 2. Membership functions for fuzzy inputs

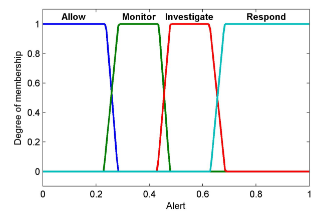


Fig. 3. Membership function for fuzzy output

C. Deffuzification

By using input variables and defined fuzzy rules, the fuzzy outputs for all rules are then aggregated to one output fuzzy set. Finally, to obtain a crisp decision value for level of alert, a defuzzification process needs to be performed. Even though there are several algorithms for this defuzzification,

TABLE I
FUZZY RULE 1∼18: LOCATION IS 'G' (GENERAL ROAD)

Rule No.	*Behaviour*	*Speed*	*Environment*	*Alert*
1 / 2:	N	Sl	Nt / C	Allow / Allow
3 / 4:	N	M	Nt / C	Allow / Allow
5 / 6:	N	F	Nt / C	Monitor / Investigate
7 / 8:	Su	Sl	Nt / C	Monitor / Allow
9 / 10:	Su	M	Nt / C	Monitor / Allow
11 / 12:	Su	F	Nt / C	Investigate / Investigate
13 / 14:	W	Sl	Nt / C	Investigate / Monitor
15 / 16:	W	M	Nt / C	Investigate / Monitor
17 / 18:	W	F	Nt / C	Respond / Respond

TABLE II
FUZZY RULE 19∼36: LOCATION IS 'R' (REGION OF INTEREST)

Rule No.	*Behaviour*	*Speed*	*Environment*	*Alert*
19 / 20:	N	Sl	Nt / C	Investigate / Monitor
21 / 22:	N	M	Nt / C	Allow / Allow
23 / 24:	N	F	Nt / C	Investigate / Monitor
25 / 26:	Su	Sl	Nt / C	Investigate / Monitor
27 / 28:	Su	M	Nt / C	Monitor / Monitor
29 / 30:	Su	F	Nt / C	Investigate / Investigate
31 / 32:	W	Sl	Nt / C	Respond / Investigate
33 / 34:	W	M	Nt / C	Investigate / Investigate
35 / 36:	W	F	Nt / C	Respond / Respond

this study uses the method of taking the centre of gravity of the aggregated output fuzzy set [12].

IV. NUMERICAL SIMULATIONS

This section carries out a numerical simulation for both synthetic and civilian traffic scenario using the proposed fuzzy expert rule-based airborne monitoring algorithm for moving ground targets using UAVs loitering over a certain area.

A. Synthetic scenario

Figure 4 shows the scenario description where a ground vehicle is moving around region of interest. In the map, at the southern area of a river, there is a stadium of strategic importance to be protected, which has a surrounding roadmap to be passed by a civilian ground vehicle near the base wall. A ground vehicle considered in this scenario circles clockwise round the stadium twice. During that time, the vehicle stops for ten seconds on the mid of road 3 near 420s. After that it crosses on the bridge and then travelling on the general road network. The vehicle trajectory data are used to generate virtual MTIR measurements composed of the relative range and azimuth angle adding the white Gaussian noise having the standard deviation of $(\sigma_r, \sigma_\phi) = (10m, 3deg)$.

The trajectory classification histories shows a reasonable performance capturing the turning or stopping manoeuvre timely as shown in Fig. 5 in conjunction with the trajectory estimation result with blue lines and numbered time history in Fig. 4. In this scenario, only road 3 and 4 are assumed to be of interest (i.e. location is 'R') as red line in Fig. 6(a), and suspicious behaviour x_s is selected as '4 4 0 0 0 0' (which means deceleration and then stopping) to detect the vehicle which stops around stadium suspiciously. In addition, the size of driving mode history y^D is set to $N_{sm} = 6$ which is the same as that of x_s.

Figure 6 shows the fuzzy rule-based decision making result including location information, behaviour cost and speed of the vehicle. Note that even if y^D and x_s are totally different, since edit distance D between them is six in this case, the lowest behaviour cost would be 1/7 instead of zero according to Eq. (8) as shown in Fig. 6(b). In normal traffic shown as blue line in Fig. 6(d), level of alert has high value when the location is 'R', behaviour cost is high as well as speed is slow. Besides, if there is congestion in the traffic, the effect of the behaviour cost and slow speed on level of alert is reduced as red line in Fig. 6(d) since those conditions are more likely to happen due to the congestion.

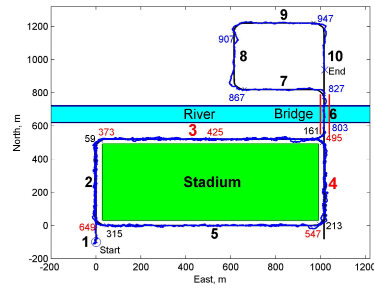


Fig. 4. Trajectory estimation for synthetic scenario

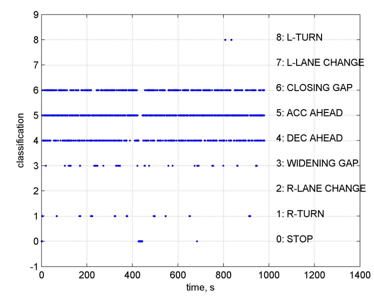
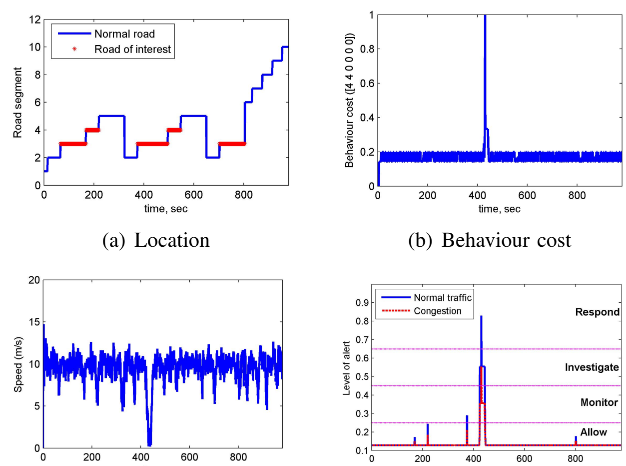


Fig. 5. Trajectory classification for synthetic scenario



(a) Location (b) Behaviour cost

(c) Speed (d) Level of alert

Fig. 6. Fuzzy rule-based decision making results for synthetic scenario

B. Civilian traffic scenario

The ground target trajectory is obtained from S-Paramics [13] traffic model of Devizes map in the UK at 2 Hz as shown in Fig. 7. Figure 8(a) shows trajectory estimation result of a given S-Paramics data with frequent lane changes inserted artificially (to generate suspicious behaviour) as shown in Fig. 8(b). This manoeuvre is called weaving or evasive, and can be viewed as one of the most dangerous behaviours in civilian traffic. In this scenario, every road is assumed to be general road (i.e. location is 'G' only), and suspicious behaviour x_s is selected as '2 7 2 7' and '7 2 7 2' (2: right lane change and 7: left lane change) to detect evasive manoeuvre.

Figure 9 shows the fuzzy rule-based decision making result including behaviour cost with trajectory classification and speed of the vehicle. In normal traffic shown as blue line in Fig. 9(d), level of alert has high value when the behaviour cost is high (which means evasive manoeuvre is likely to be happening) around 20∼40 seconds or velocity is fast around 10 second. In case there is congestion as red line in Fig. 9(d), although level of alert shows the same tendency, the effect of the behaviour cost is reduced as frequent lane change is more likely to happen due to the congestion. On the contrary, the effect of fast speed is enhanced around 10 second since fast ground vehicle in the congested traffic could be regarded as dangerous one.

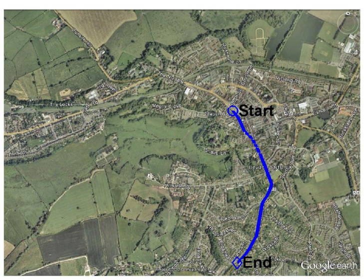
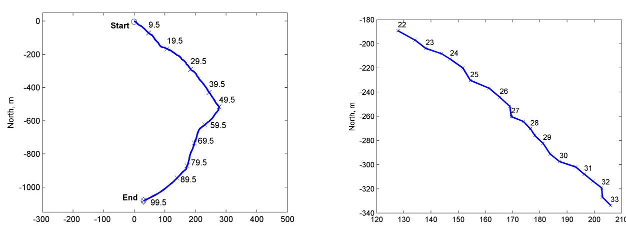


Fig. 7. Trajectory of a ground vehicle within the Devizes road network with GIS satellite data overlaid thanks to Google earth



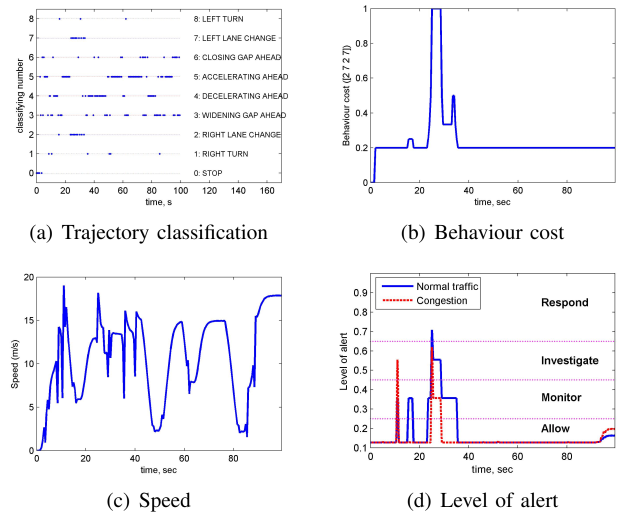
(a) Entire trajectory

(b) Evasive manoeuvre part

Fig. 8. Trajectory estimation result and artificial evasive manoeuvre

V. Conclusions

This paper proposed a fuzzy expert rule-based airborne monitoring methodology of ground vehicle behaviour to identify suspicious or abnormal behaviour considering spatiotemporal environment factors as well as behaviour itself. Numerical simulation results using synthetic scenario and realistic car trajectory data showed the feasibility of the proposed approach successfully providing a recommended level of alert. The study could be applied to various scenarios in view of both military and civil applications: monitoring urban/rural area of interest, detecting unknown intent of terrorists, providing a protective surveillance around military facilities, and enhancing situational awareness of traffic movements both on land and at sea. As a future work, additional relevant aspects of behaviour will be considered as fuzzy inputs such as cultural background related to driving habits and deviation from general behaviour.



(a) Trajectory classification

(b) Behaviour cost

(c) Speed

(d) Level of alert

Fig. 9. Fuzzy rule-based decision making result for civilian traffic scenario

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