Signal Processing Solutions for a Networked Battlespace

L_WP2.1: Ground vehicle tracking aided by geologic information

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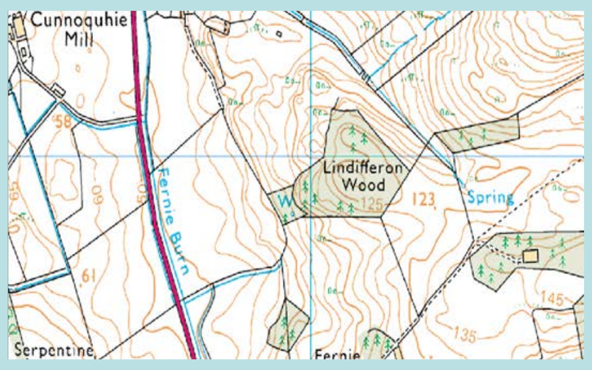
Objectives of the work package:

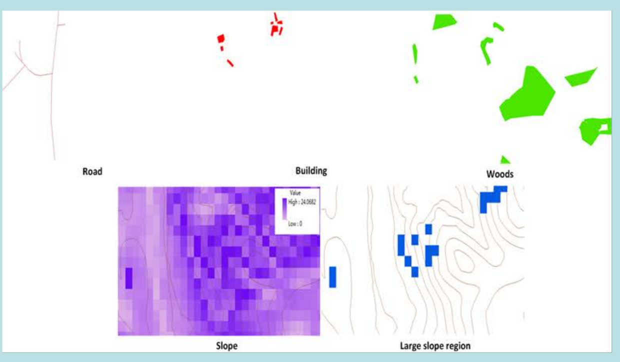
- A framework to explore all the previously collected information and data available for moving platforms in a networked environment when performing signal processing will be developed
- New signal processing algorithms offering adaptivity to operational environments will be developed by exploiting domain knowledge.
- Extension will be made to multiple sensor platforms operating in a networked environment by fusing different types of information.

Geologic layer information:
For a real scenario, there is much information available, such as road, woods, buildings and height information, which constrains the movement of a vehicle:



- The movement of the vehicle is constrained by the road when it moves on-road
- The movement of the vehicle is constrained by the infeasible region when it moves off-road

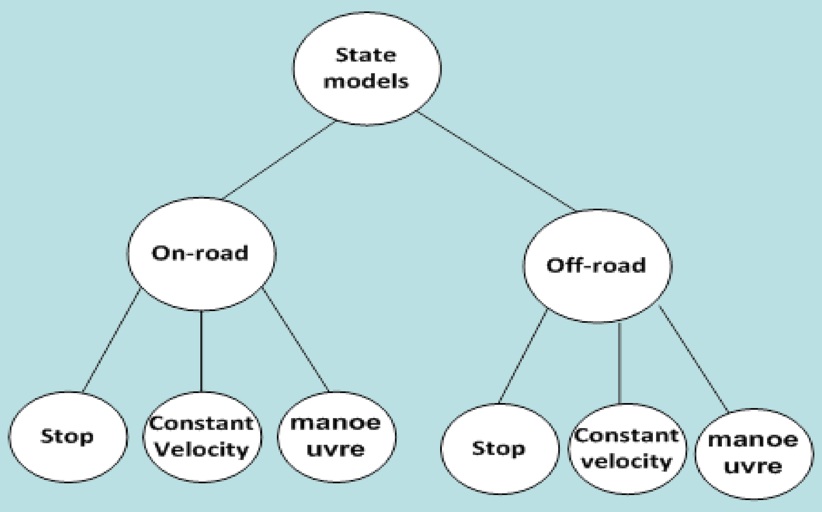
Geologic information can be obtained from the on-line available datasets, from the Geographic Information System (GIS), different geologic layers can be extracted:



Different layers

Overlapping of layers and original scene

Multiple state models for vehicle tracking:



Multiple state models are needed for the vehicle tracking problem:

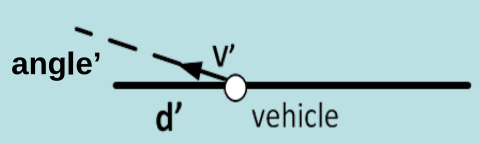
- In order to better use the geologic information, separate state models for on-road movement and off-road movement are applied
- The vehicle moves in different ways: stop, constant velocity and manoeuvre
- The state vector is represented as $(X_t, \{r_t, l_t\}, m_t)$

Off-road model: X_t is denoted as $X_t^{offroad}$ and: $X_t^{offroad} = F_{offroad} X_{t-1}^{offroad} + G_{offroad} W_{offroad}$

On-road model: X_t is denoted as X_t^{onroad} and: $X_t^{onroad} = F_{onroad} X_{t-1}^{onroad} + G_{onroad} W_{onroad}$

Transition probabilities between on-road and off-road models:

$$p(r_t = onroad | r_{t-1} = offroad, X_{t-1}^{offroad}) = \begin{cases} 0 & if\ angle > th1\ or\ \left(\frac{d}{v}\right) > th2 \\ \exp\left((-c1) * angle + (-c2) * \left(\frac{d}{v}\right)\right) & else \end{cases}$$



$$p(r_t = offroad | r_{t-1} = onroad, X_{t-1}^{onroad}) = \begin{cases} 0 & if\ angle' > th1\ or\ \left(\frac{d'}{v'}\right) > th2 \\ \exp\left((-c1) * angle' + (-c2) * \left(\frac{d'}{v'}\right)\right) & else \end{cases}$$

Transition probabilities between different movement types:

If $(\text{velocity} < thre)$: $p(m_t = stop | m_{t-1}) = p(m_t = CV | m_{t-1}) = p(m_t = \text{manoeuvre} | m_{t-1}) = \frac{1}{3}$

Else: $p(m_t = stop | m_{t-1}) = 0 \quad p(m_t = CV | m_{t-1}) = p(m_t = \text{manoeuvre} | m_{t-1}) = 1/2$

Finite-set measurement for airborne GMTI:

A GMTI radar can measures the relative range r and azimuth angle θ as:

$$\begin{pmatrix} r \\ \theta \end{pmatrix} = \begin{pmatrix} \sqrt{(x_{UAV} - x_{vehicle})^2 + (y_{UAV} - y_{vehicle})^2 + (z_{UAV} - z_{vehicle})^2} \\ \operatorname{atan}((y_{UAV} - y_{vehicle})/(x_{UAV} - x_{vehicle})) \end{pmatrix} + \begin{pmatrix} n_r \\ n_\theta \end{pmatrix}$$

Two problems exist with the GMTI radar:

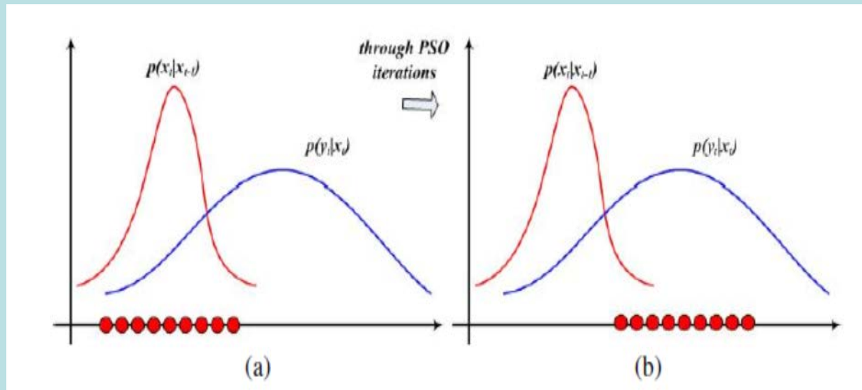
- Miss detection
- False alarms

Finite-set measurement theory is introduced to incorporate the miss detection and false alarms into the measurement model:

$$f(Z|X_t) \propto 1 - P_D(X_t) + P_D(X_t) \sum_{z \in Z} \frac{f(z|X_t)}{\gamma \cdot c(z)}$$

Tracking algorithm:

Particle filtering algorithm is applied, with particle swarm optimization (PSO) being introduced to make the samples converge to the high measurement likelihood region.



For n=1,….,T

$$v^{i,n+1} = |r_1|(p^i - X_t^{i,n}) + |r_2|(g - X_t^{i,n}) + \rho$$

$$X_t^{i,n+1} = X_t^{i,n} + v^{i,n+1}$$

with

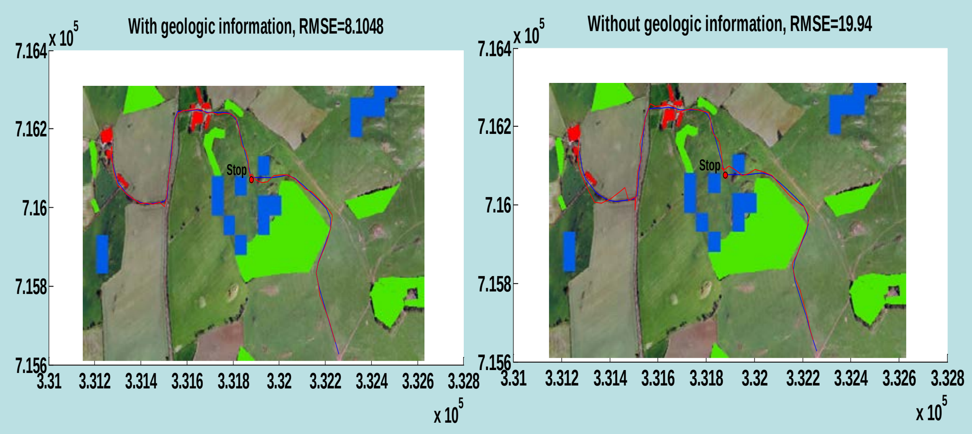
$$p^i = \begin{cases} X_t^{i,n+1} & if\ f(Z|X_t^{i,n+1}) > f(Z|p^i) \\ p^i & else \end{cases}$$ and

$$g = argmax_{\ p^i} f(Z|p^i)$$

Experimental evaluation:

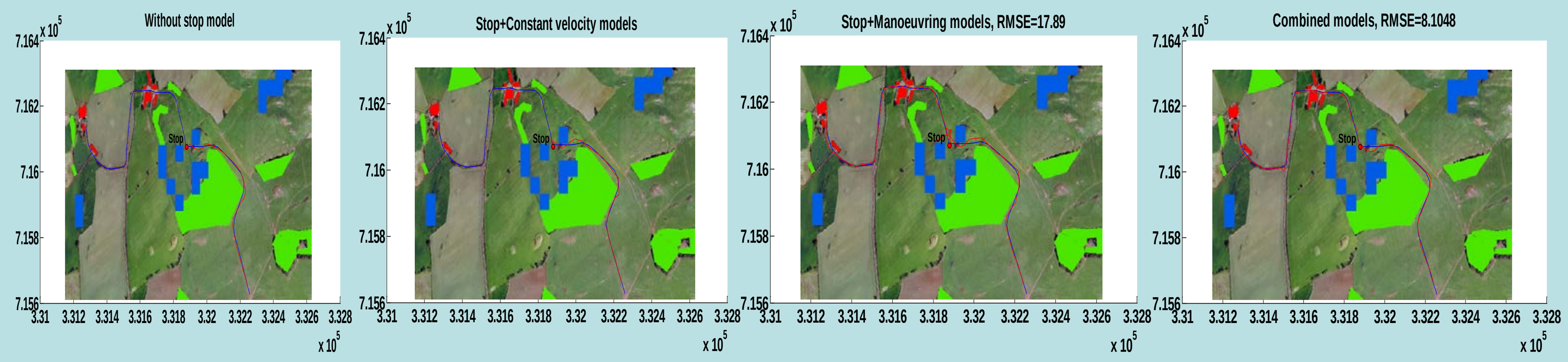
A vehicle is simulated to move on the ground with different movement types, and a UAV is simulated to cruise at an altitude of 200m to monitor this area, the circle radius is 100m and the angular speed of the UAV is $(\pi/20)$.

Comparison with/without geologic information:



	No. of successful tracks	Mean of the RMSEs	Standard deviation of RMSEs
Tracking without domain knowledge	20/30	24.57	17.06
Tracking with the domain knowledge	30/30	9.35	2.62

Advantages of applying multiple models:



	No. of successful tracks	Mean of the RMSEs	Standard deviation
Tracking without stop model	16/30	19.88	7.08
Tracking with stop model	30/30	9.35	2.62

	No. of successful tracks	Mean of the RMSEs	Standard deviation
Stop &Constant Velocity models	0/30	---	---
Stop&Manoeuvring models	27/30	15.25	5.06
Tracking with all the three models	30/30	9.35	2.62

Comparison between different algorithms

Comparisons are made between the multiple models particle filter (MM-PF), its improved version (multiple models auxiliary particle filter, MM-APF) and our proposed algorithm (MM-PSO-PF):

	No. of successful tracks	Mean of the RMSEs	Standard deviation of the RMSEs
MM-PF	20/30	14.99	5.17
MM-APF	26/30	16.02	3.99
MM-PSO-PF	30/30	9.35	2.62

Conclusions and future works:

In this work:

- The available geologic information is applied as the domain knowledge
- The vehicle can move both on-road/off-road and move in different movement types, multiple state models are considered.
- We consider a more realistic measurement model of the GMTI radar by considering both miss detection and false alarms.
- We proposed a MM-PSO-PF scheme, which adopts a new sampling scheme by making the samples converge to the high measurement likelihood region and better results are obtained

In next steps, we will:

- Consider the tracking scenario in an urban environment, a Bernoulli filter will be applied and PSO scheme will be applied to improve the performance of traditional Bernoulli filter.
- Tracking of the vehicle will be combined with the path optimization to make the UAV follow the vehicle in an urban environment, and corresponding simulations will be made from a real city scenario or battlefield environment.

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