Multiple ground targets tracking using negative information

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Abstract: Multiple targets tracking with a GMTI is a challenging problem for the battlefield surveillance. A new algorithm is used in order to track multiple manoeuvring ground targets with road constraint. However, the case of non-detected targets due to the ground context is not tacking in account in the target tracking process. In this paper, we present our approach to track ground targets with the possibility to the target to be non-detected.

1 Introduction

This paper focuses on the multiple targets tracking with the negative information using Ground Moving Target Indicator (GMTI). The negative information [UK06] is the non-detection, which results, for instance, by the deliberately ground target stop. Kirubarajan *et al.* consider this information in [KB00], and propose to palliate the stop manoeuvre by introduce a stop motion model in a usual IMM. This technique has been enlarging by tacking in account the road network in the ground target tracking process. The proposed algorithm, presented in [PNR06], is an IMM under road constraint with a variable structure (called VS IMMC) to anticipate the manoeuvre of the target on the road. However, due to the terrain elevation and the road network configuration, the ground targets can be non-detected and moving on the road network. In fact, the terrain elevation or vegetation generates a terrain mask in which the targets are hided. In addition, the sensor does not detect the ground targets when their radial velocity falls under the Minimal Detection Velocity (MDV) fixed by the sensor. The radial velocity depends on the velocity heading given by the road direction and the sensor location. If the terrain obscuration condition is not tacking in account, the VS IMMC losses the track when the target is masked or non-detected due to its radial velocity, because the stop motion model of the VS IMMC is activated in despite of the movement of the target.

One issue of this problem is to introduce in the VS IMMC the event on the perceivability on the target. Dezert and Rong Li in proposed this idea [DNR99]. However, the perceivability probability does not take in account the sensor's MDV and the terrain obscuration. Therefore, we proposed to introduce in this paper the prior information on the target's perceivability to keep the track and do not activate the stop motion model in a multi-target context when the target is masked.

This paper is organized as follows: in a second part, we introduce the perceivability probability in the likelihood of a track. In a third part, we present the different type of masks and we create the prior information according to the type of mask, and we describe an approach, called "sentinel", to track multiple target in the same mask. Finally, we present an example and give a brief conclusion.

2 Introduction of the perceivability probability in the target tracking process

At time *k*, the target state perceivability is represented by the exhaustive and exclusive events:

$$O_k = \{\text{target is perceivable}\} \text{ and } \bar{O}_k = \{\text{target is unperceivable}\}$$

O_k will denote both the target can be detected by the sensor and the random event. By introduce the both event in the conventional IMM, we obtain a new formulation of the likelihood function. In the conventional IMM, we have for each $\mathrm{M}_s^i(k)$ motion model beyond *r*+1 motions models $\left(\forall i \in \{0,...,r\}\right)$:

$$\Lambda_i(k) = p\left\{z(k) \middle| Z^{k-1,n}, \theta^{k,l}, M_s^i(k)\right\}$$

where $z(k)$ is the MTI report, $Z^{k-1,n}$ a sequence of previous measurement, $\theta^{k,l}$ the event associate to the track generates by the sequence *l* of measurement $Z^{k,l}$ where $Z^{k,l} = \left\{Z^{k-1,n}, z(k)\right\}$, and $M_s^i(k)$ the event assoiate to the motion model $\mathrm{M}_s^i(k)$ used by the target. By tacking the notation given in [BNR06], *i* represents the number of the motion model and *s* is the road segment on which the model $\mathrm{M}^i(k)$ is constrained. Now due to the total probability rules, we introduce the event that the target is detected $\{m=1\}$ or not $\{m=0\}$ and the events O_k and $\bar{O}_k$. We obtain $\left(\forall i \in \{0,...,r\}\right)$:

$$\begin{aligned}\Lambda_i(k) = {} & p\left\{z(k), m=1, O_k \middle| Z^{k-1,n}, \theta^{k,l}, \mathrm{M}_s^i(k)\right\} + p\left\{z(k), m=1, \bar{O}_k \middle| Z^{k-1,n}, \theta^{k,l}, \mathrm{M}_s^i(k)\right\} \\ & + p\left\{z(k), m=0, O_k \middle| Z^{k-1,n}, \theta^{k,l}, \mathrm{M}_s^i(k)\right\} + p\left\{z(k), m=0, \bar{O}_k \middle| Z^{k-1,n}, \theta^{k,l}, \mathrm{M}_s^i(k)\right\}\end{aligned}$$

However, an unperceivable target can not be detected. So the event $\left\{m=1,\bar{O}_k\right\}$ is equal to $\{\varnothing\}$. According to the Kirubarajan approach, we distinguish the motion model STOP from the set of motion models. Then the event $\left\{M_s^0(k),m=1\right\}$ is equal to $\{\varnothing\}$ because the stop motion model don't must be activated if there is a detection. By using the Bayes rule, we find the new expression of the likelihood function $\left(\forall i\in\{1,...,r\}\right)$:

$$\begin{aligned}\Lambda_i(k)=&\left(1-\delta_{m,0}\right)\cdot P_D\cdot p\left\{z(k)\middle|Z^{k-1,n},\theta^{k,l},M_s^i(k),O_k\right\}\cdot P\left\{O_k\middle|Z^{k-1,n},\theta^{k,l},M_s^i(k)\right\}\\&+\left(1-P_D\right)\cdot\delta_{m,0}\cdot P\left\{O_k\middle|Z^{k-1,n},\theta^{k,l},M_s^i(k)\right\}+\delta_{m,0}\cdot\left(1-P\left\{O_k\middle|Z^{k-1,n},\theta^{k,l},M_s^i(k)\right\}\right)\end{aligned}$$

$$\Lambda_0(k)=\delta_{m,0}\cdot P\left\{O_k\middle|Z^{k-1,n},\theta^{k,l},M_s^0(k)\right\}$$

if , the perceivability probability $P\left\{O_k\middle|Z^{k-1,n},\theta^{k,l},M_s^i(k)\right\}$ $\left(\forall i\in\{0,...,r\}\right)$ is equal to one, we find the likelihood expression given in , *i.e.* the algorithm take only in account the non-detection due to the stop of the target. On the contrary, if the perceivability probability $P\left\{O_k\middle|Z^{k-1,n},\theta^{k,l},M_s^i(k)\right\}$ $\left(\forall i\in\{0,...,r\}\right)$ is equal to 0 the stop motion likelihood is equal to 0 and the likelihood from each motion model is equi-probable that provocates the keep of track during the target is hidded. Now, we must calculate the perceivability probability from each motion model.

3 Terrain masks definition and perceivability probability calculation

In this part, we present the different reasons due to the target non-detection. We consider in this paper that the target is unperceivable by the GMTI sensor because the target is either hidden by the terrain elevation (this masks is noted Ma_1), or either the radial target velocity is less than the MDV (this masks is noted Ma_2). So for each motion model we have $\left(\forall i\in\{0,...,r\}\right)$:

$$P\left\{\bar{O}_k\middle|Z^{k-1,n},\theta^{k,l},M_s^i(k)\right\}=P\left\{M_{a_1}(k)\cup M_{a_2}(k)\middle|Z^{k-1,n},\theta^{k,l},M_s^i(k)\right\}$$

where $\left\{M_{a_1}(k)\right\}$ and $\left\{M_{a_2}(k)\right\}$ are the events associate the unperceivability du to the mask Ma_1 and Ma_2 respectively. By using the Poincaré formula and the independence between the two events, we obtain the unperceivability prior probability from each type of mask.

The prior unperceivability probability of the mask due to the terrain elevation is evaluated thanks to the digital terrain elevation data called DTED. Knowing the location of the sensor and the DTED, it is possible to compute a binary picture I, which indicate the non-detection areas. Starting with the predicted state $\hat{x}_{i,s}(k|k-1)$ under constraint from each motion model and its associate covariance $P_{i,s}(k|k-1)$, we obtain the target location (c_x, c_y) and the location covariance Pp in the picture, according to the transformation function $T_{R \to I}$ between the real location and the picture I. Due to the uncertainty on the target location, we propose to take in account a neighborhood of (c_x, c_y) in order to know if the target is unperceivable. Finally, the prior unperceivability probability is equal to :

$$P\left\{M_{a_2}(k)\middle|Z^{k-1},\theta^{k,l},M_s^i(k)\right\}=\sum_{i=1}^{L}\sum_{j=1}^{L}H_{\hat{x}_{i,s}(k|k-1)}(i,j)\cdot I\left(c_x+i-\left\lfloor\frac{L}{2}\right\rfloor-1,c_y+j-\left\lfloor\frac{L}{2}\right\rfloor-1\right)$$

where, $H_{\hat{x}_{i,s}(k|k-1)}$ is the Gaussian distribution on the picture centered in (c_x, c_y),

$$H_{\hat{x}_{i,s}(k|k-1)}(i,j)=\frac{1}{\sqrt{|2\cdot\pi\cdot\mathrm{Pp}|}}\times\exp\left(-\frac{1}{2}\cdot\left(\begin{bmatrix}i\\j\end{bmatrix}-\begin{bmatrix}c_x\\c_y\end{bmatrix}\right)'\cdot\mathrm{Pp}^{-1}\cdot\left(\begin{bmatrix}i\\j\end{bmatrix}-\begin{bmatrix}c_x\\c_y\end{bmatrix}\right)\right)$$

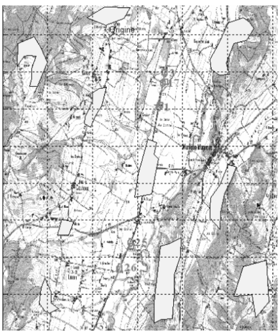
The value L is the gate equal to the maximum standard deviation of Pp and $\lfloor . \rfloor$ symbolizes the integral part.

Now, we calculate the prior unperceivability probability that the target can be detected due to its radial velocity, which is inferior to the MDV. According to a Gaussian distribution, the predicted radial velocity $\dot{\rho}_i^l(k|k-1)$ from each track and each motion model given in [LBK04] is evaluated, and the probability that the radial velocity is under the MDV can be calculated.

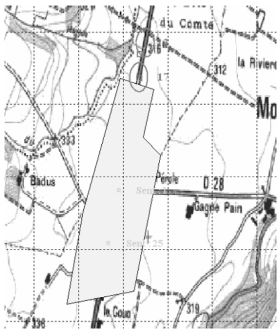
$$P\left\{M_{a_2}(k)\middle|Z^{k-1,n},\theta^{k,l},M_s^i(k)\right\}=P\left\{0<\dot{\rho}_i^l(k|k-1)<MDV\middle|Z^{k-1,n},\theta^{k,l},M_s^i(k)\right\}$$

Consequently, the prior unperceivability probability can be calculated. In the particular case, where the system track only one target in a terrain mask, the proposal approach is sufficient. However, when several targets are in the same mask, the kinematics information is not sufficient to discriminate the targets in the mask. That is why we use a "sentinel" to attach a track. A "sentinel" is a special state who replaces the head of the tracks when the perceivability probability is near 0. Then when the "sentinel" is activated, this special state is automatically placed at the exit of the mask and waits for the MTI report of the target, like a cat who is waiting for a mouse to come out of cover (thank you Mr. Koch for your metaphor). Then, a new track is build with the probability to attach this new track to the "sentinel".

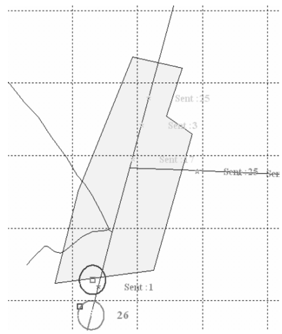
We illustrate our approach by the following example. We consider five targets on the road and they approach a terrain mask (Picture 1). In the Picture 2, the tracks 1 and 25 are in the terrain mask and the corresponding states are placed in a "sentinel" configuration. Afterwards, the "sentinels" are activated at the exit of the mask awaiting a new MTI report. Then a new track is build (Picture 3) with the probability to associate the MTI report to an activated "sentinel". If there is no ambiguity association between the sentinel and the new track, the system decides to attach the old track to the new track. In the other hand, the system takes no decision.



Picture 1.



Picture 2.



Picture 3.

Conclusion

The originality of the proposal approach is the modelization of the negative information, which depends on three phenomenons: the stop of the target, the hidden targets due to the terrain elevation or the radial velocity inferior to the MDV. We have introduced these informations in the Kirubarajan's algorithm [KB00]. Afterwards we have enlarged this last one in a multiple target context. Then, the concept of "sentinel" is proposed to attach a track to a MTI report at the exit of the mask. More investigations must be made on real data in order to validate our algorithm.

References

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