

Improved multi-target classification

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Introduction

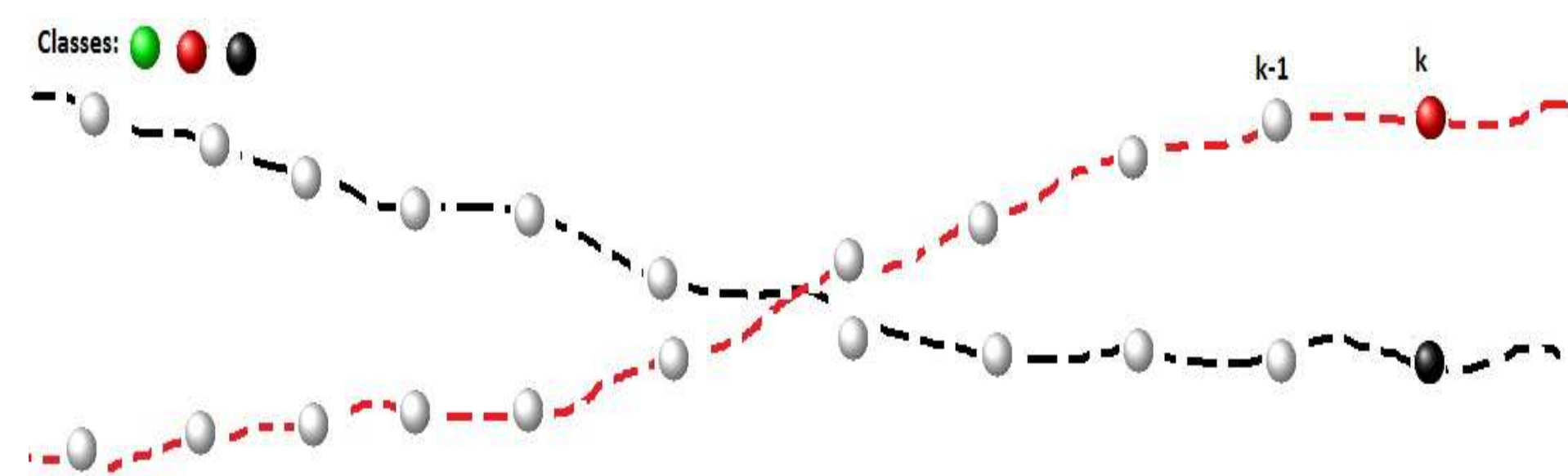
Objective: manœuvring multiple targets tracking and correct classification



Difficulties:

- association of measures and predictions
- adaptive estimation of the state of all targets
- (dis)appearance of targets
- correct and robust classification of the targets

Problem description

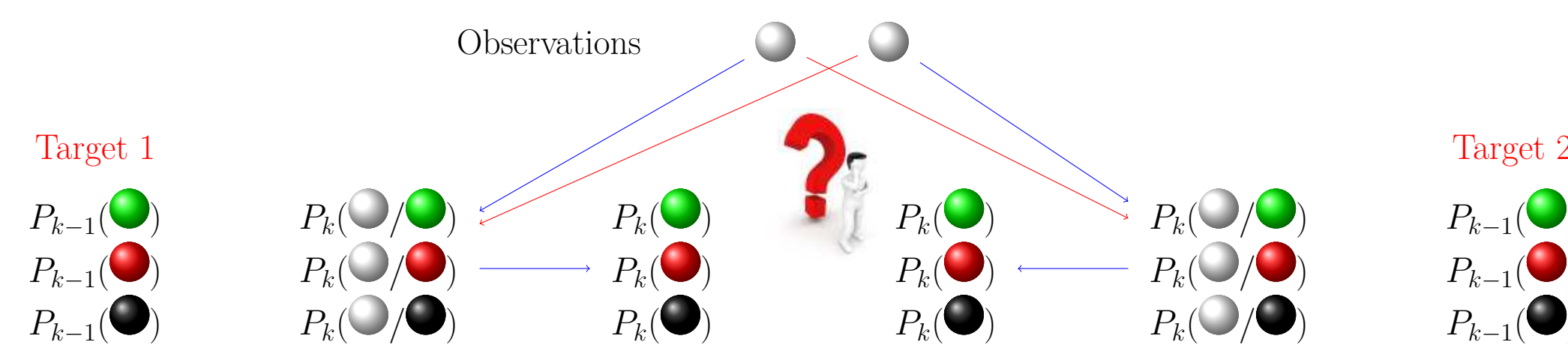


- targets: white balls
- targets trajectories: dashed lines
- targets classes: colored balls

Single target classification illustration

Time ($k-1$)	Sensor: likelihood	Time (k)
$P_{k-1}(\text{green}) = 0.3$	$P_k(\text{green}) = 0.7$	$P_k(\text{green}) = 0.6$
$P_{k-1}(\text{red}) = 0.3$	$P_k(\text{red}) = 0.1$	$P_k(\text{red}) = 0.1$
$P_{k-1}(\text{black}) = 0.4$	$P_k(\text{black}) = 0.2$	$P_k(\text{black}) = 0.3$

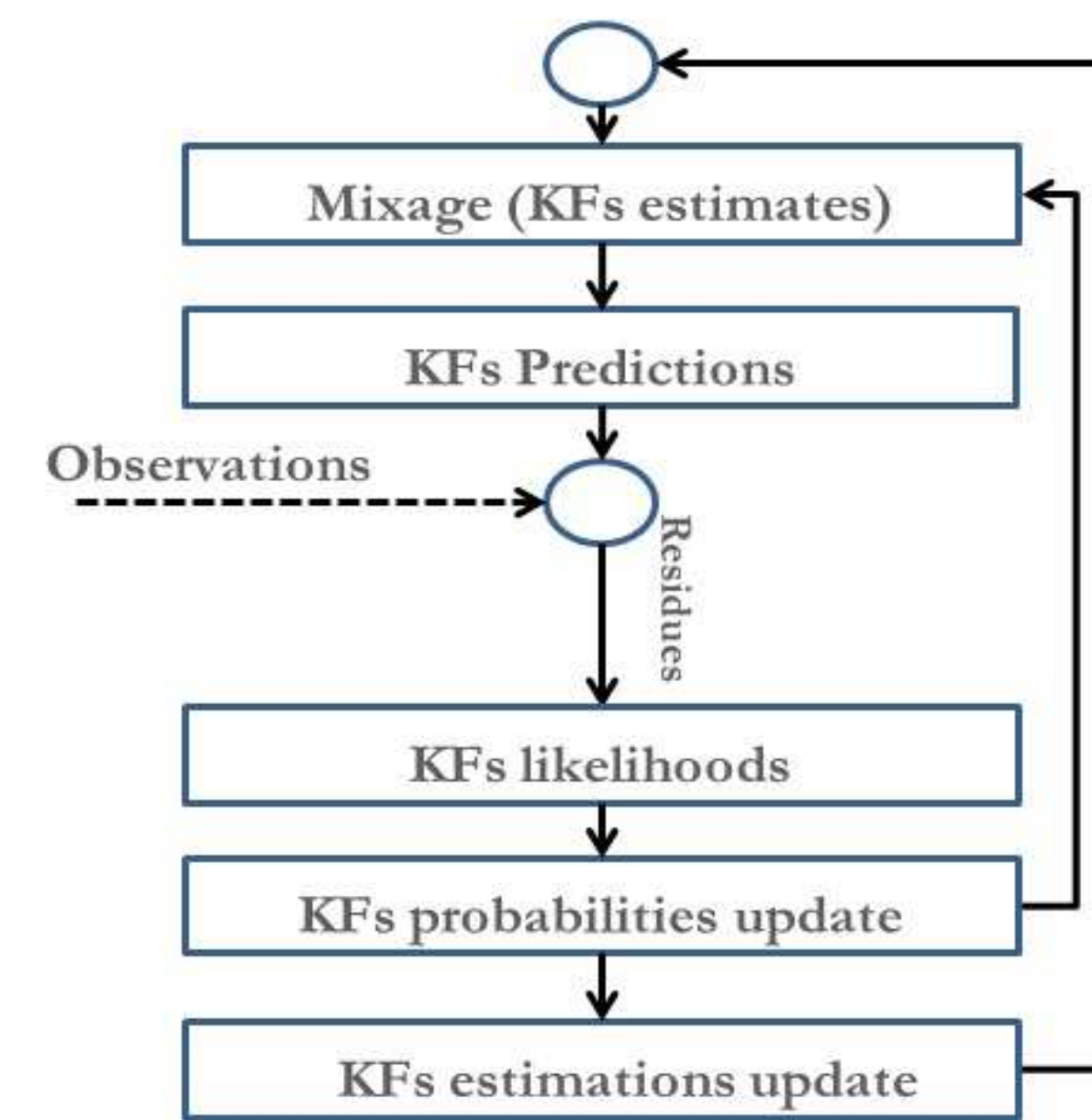
Two targets classification: association problem



Solution

Targets tracking

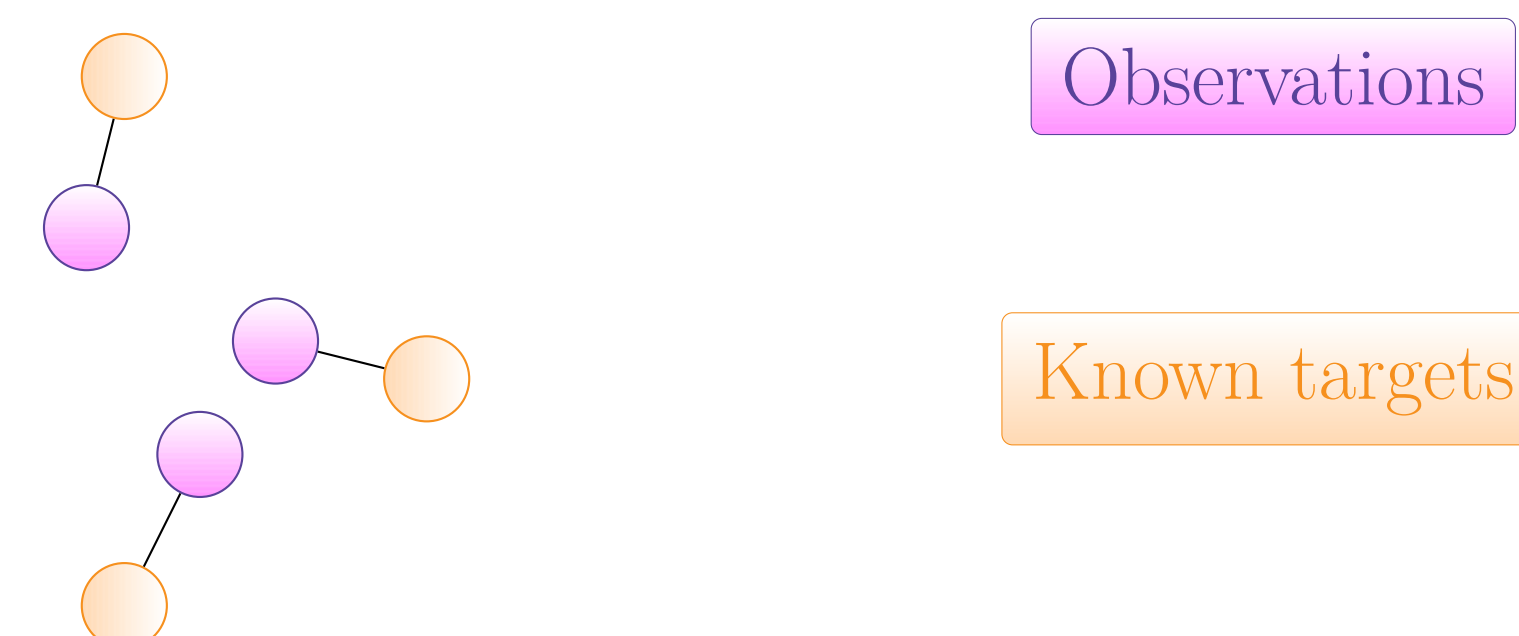
The adaptive estimation of one target's movement is ensured by a set of Kalman filters (KFs) (one Kalman filter for one evolution mode). Kalman filters are executed in parallel, they form an Interacting Multiple Model (IMM) algorithm (one IMM to track one target)



Assignment problem

Assignment of m Observations z to n targets $\hat{z}$.

- Known targets: $\hat{z}_i, i = 1, \dots, n$
- Observations: $z_j, j = 1, \dots, m$
- Assignment matrix calculation
- Assignment matrix resolution with Munkres algorithm
- Output results: $(\hat{z}_i, z_j)$



Classification algorithms

Standard algorithm (Bayesian)

- Input : *a priori* probabilities $P_{k-1}(c_i)$ and Likelihoods $\lambda(c_i)$ of the classes $c_i \in C$, with $i = 1, \dots, S$
- Bayesian Theorem (BT) :

$$P_k(c_i) = \frac{\lambda(c_i)}{\sum_{j=1}^S \lambda(c_j) P_{k-1}(c_j)} P_{k-1}(c_i)$$

- Output : classes probabilities at time k :

$$P_k(c_i), i = 1, \dots, S$$

Advanced algorithm (Belief)

- Algorithm based on belief functions (1980's)
- It is a non additive model
- Proba: $P(A \cup B) = P(A) + P(B), \text{ if } A \cap B = \emptyset$
- Belief: $Bel(A \cup B) \neq Bel(A) + Bel(B)$
- More complex but more precise and robust

Example of maritime piracy

Classes definition

- Cargo: constant speed
- Military boat: constant speed, medium acceleration
- Go-fast boat: constant speed, medium or sharp acceleration

Simulated scenario

- Target 1: constant speed $\rightarrow$ sharp acceleration
- Target 2: constant speed $\rightarrow$ medium deceleration $\rightarrow$ sharp acceleration
- Target 3: appears $\rightarrow$ constant speed $\rightarrow$ sharp deceleration $\rightarrow$ disappears

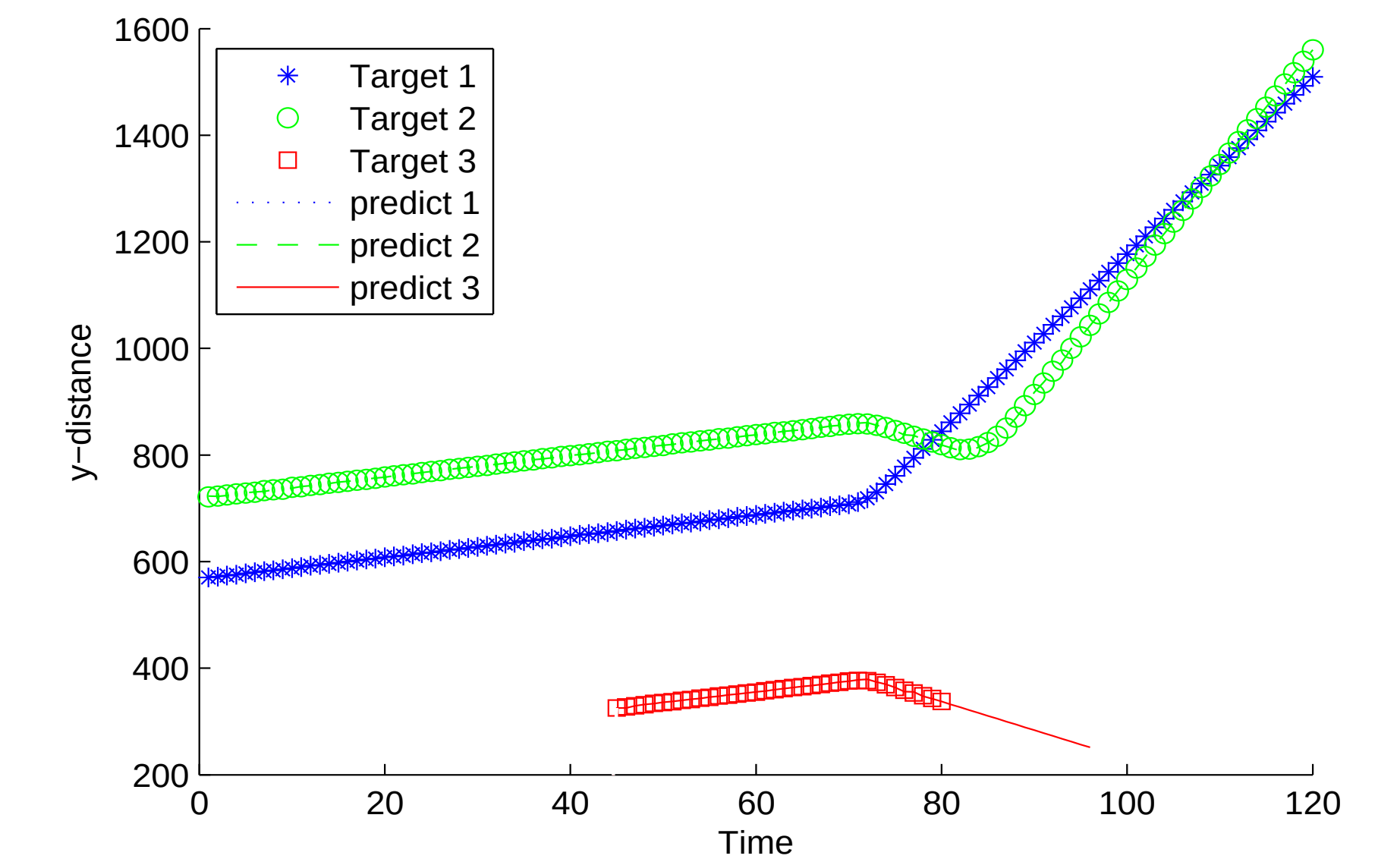
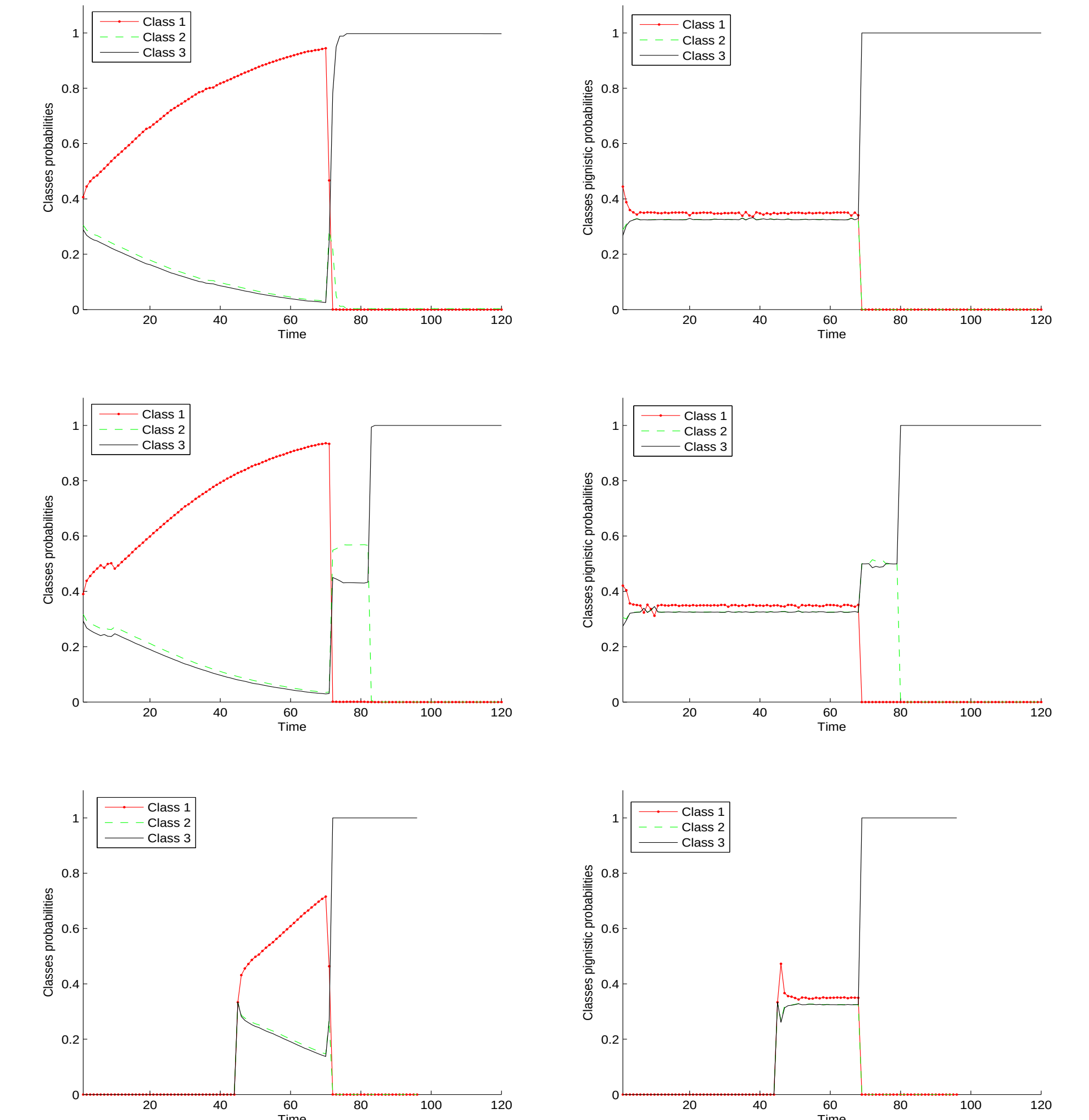


Figure: simulated scenario

Classification results



Targets 1, 2 and 3 classifications:

- left: standard (Bayesian) classification
- right: advanced (belief) classification

Some conclusions

- Advanced algorithm (belief functions) highly improves the results
- In the future, will use extra data such as shape of fleets or flying squadrons
- Can be applied to a wide variety of applications provided a model of targets' evolution (pedestrian recognition...)