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AI SOLUTIONS FOR BUSINESS

Deep Recurrent Neural Network for Multi-target Filtering

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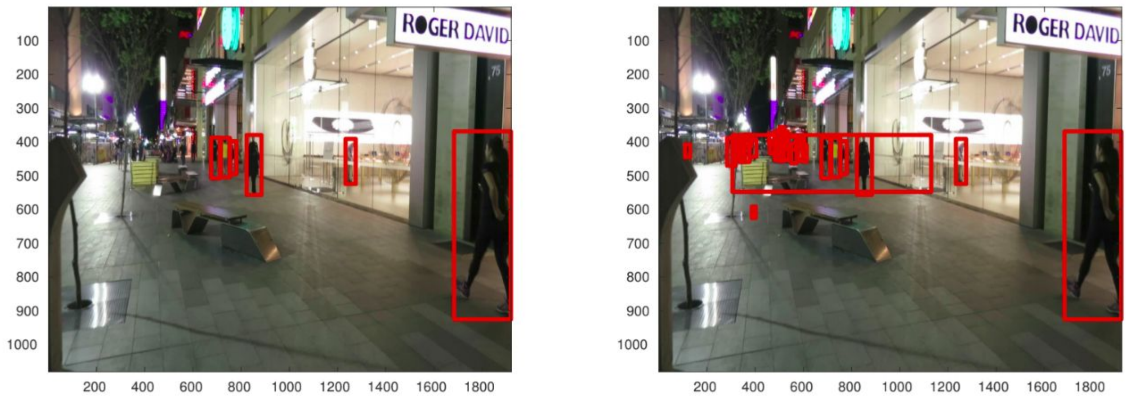
Multi-target filtering: definition & applications

- A multi-target filtering algorithm removes clutter (false positive) from a sequential data.
- Examples:
  - Stereo vision
  - Radar/LiDAR signal analysis
  - Robotics: SLAM and occupancy grid
  - Object detection and tracking



- Example of multi-target filtering usage: varying detection threshold to increase TPR

Multi-target filtering: algorithms

$$p_k(x_k|z_{1:k}) = \frac{g_k(z_k|x_k)p_{k|k-1}(x_k|z_{1:k-1})}{\int g_k(z_k|x)p_{k|k-1}(x|z_{1:k-1})dx}$$

- Kalman Filter (KF) based techniques:
  - Gaussian and linear motion model assumptions.
  - Extended KF: Linearisation via Taylor series expansion to maintain Gaussian behaviour
  - Unscented KF: Deterministic selection of sample at different variances along each dimension to compute covariance and mean for an estimated Gaussian function.
- Information Filter (IF)
  - Similar to KF, but works on canonical space (inverted covariance, i.e. information matrix)
  - SEIF: unlike the covariance matrix, the information matrix is very sparse. SEIF uses this sparsity to discard significant number of landmarks at each iteration, improving computation time.
- Particle filter
  - Estimates the posterior using Monte Carlo technique. Can handle non-linear non-Gaussian models.
- Neural networks:
  - Recurrent neural networks
    - Long short-term memory

Multi-target filtering: challenges

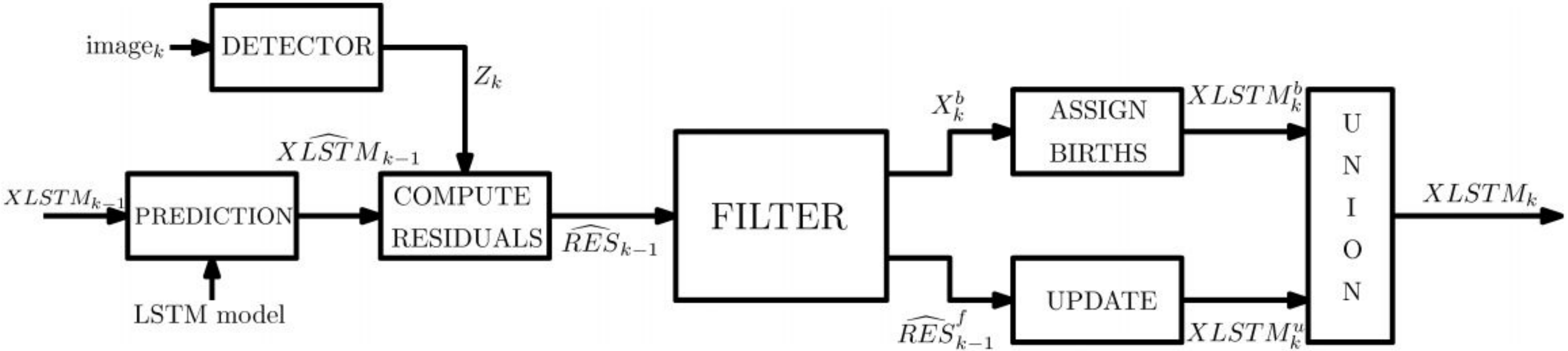
$$p_k(X_k|Z_{1:k}) = \frac{g_k(Z_k|X_k)p_{k|k-1}(X_k|Z_{1:k-1})}{\int g_k(Z_k|X)p_{k|k-1}(X|z_{1:k-1})\mu_s(dX)}$$

- Extension to multi-target:
  - Random finite sets (RFS) and Probability Hypothesis Density (PHD)
    - Mapping the multi-target state vectors to a universal single target problem
- Fixed motion model issues:
  - Complex non-linear motion (can happen in presence of a noisy detector) can lead to wrong predictions.
- Gaussian assumption, especially in KF-PHD
- Challenges in using sequential learning algorithms:
  - Unlike the Bayesian generative models, they rely on a separate train/test steps
  - Cluttered unlabelled data can lead to weak predictive models
  - Variable input size
  - Memory management

Proposed multi-target filtering algorithm

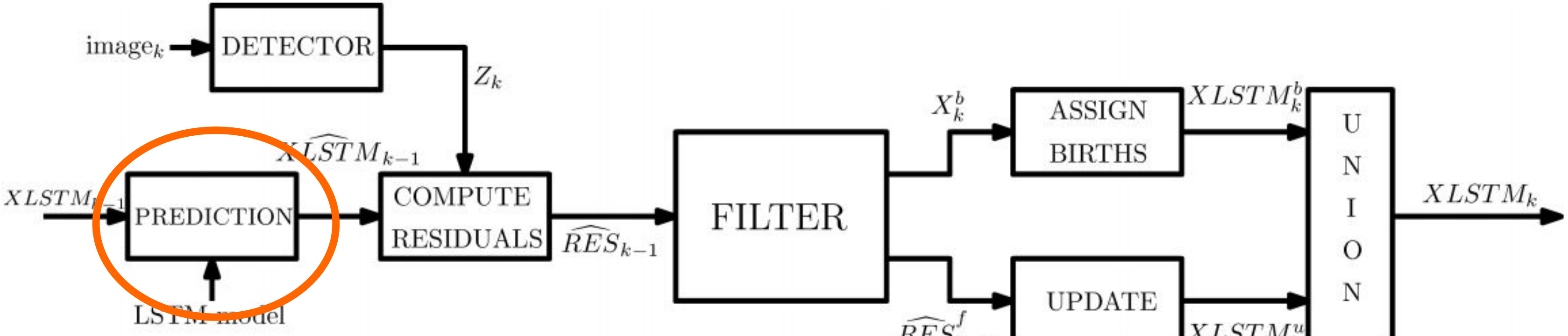
Proposed algorithm

- The proposed algorithm addresses the following problems:
  - Handing non-linear non-Gaussian multi-target motion
  - Does not rely on a fixed motion model and it learns it incrementally
  - Use of neural networks (an example of a sequential learning algorithm) for filtering



Proposed algorithm: prediction step

- A target tuple is defined as: $xlstm = (x \in X_k, m_k \in \mathbb{Z}, g_k \in \mathbb{R}^+, f_k \in \{0,1\})$
- The model initially is trained to act as an auto-encoder regressor.
- Once the model is trained, it is transferred to the other target, saving time and memory.

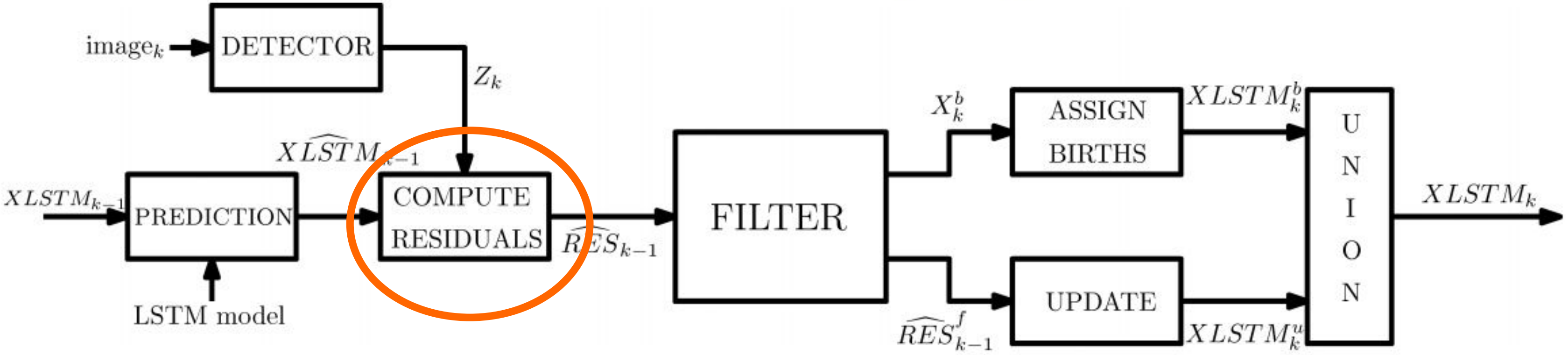


Proposed algorithm: data association & filtering

- Using the incoming measurement RFS a set of residual tuples are computed:

$$\hat{res} = \left(\hat{xlstm} \in XLSTM_{k|k-1}, T \in \mathbb{R}^+, z \in Z_k\right)$$

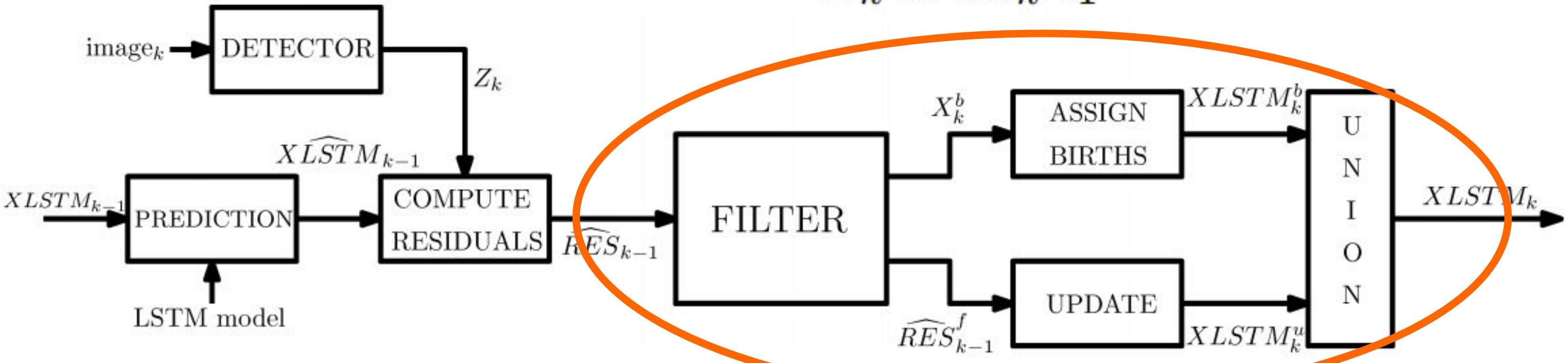
$$\|\hat{x} - z\|_2$$



Proposed algorithm: data association & filtering

- Computing all the 'targetness' error T for all measurements and targets creates a matrix:

$$T_{k|k-1} \rightarrow N_k \times M_{k-1}$$



Proposed algorithm: Update

- Using the targetness matrix:

$$C^I_{k|k-1} = \underset{\hat{m}_k}{\operatorname{argmin}} \left(T_{k|k-1}\right), \qquad R^I_{k|k-1} = \underset{n_k}{\operatorname{argmin}} \left(T_{k|k-1}\right)$$

$$mg_{k|k-1} = \min_{\hat{m}_k} \left(T_{k|k-1}\right), \qquad g_{k|k-1} = \min_{n_k} \left(T_{k|k-1}\right)$$

$$H^{C^I}_{k|k-1} = \operatorname{hist}(C^I_{k|k-1}), \qquad H^{R^I}_{k|k-1} = \operatorname{hist}(R^I_{k|k-1})$$

- Then the following data association algorithm is used assign target survival (true positivity), death (false positivity) and birth →

Input: $m_{min}, g_{min}, g_{max}, H^{C'}_{k|k-1}, H^{R'}_{k|k-1}, g_{k|k-1}, mg_{k|k-1}$, $XLSTM_{k|k-1}, Z_k$

Output: Survived targets and births: $RES^f_{k|k-1}$ and X^b_k

% Iterate over M_{k-1} targets in $XLSTM_{k|k-1}$:

for $\hat{m}_k = 1, 2, \dots, M_{k-1}$ **do**

  if $(H^{C^I}_{k|k-1}(\hat{m}_k) == 0$ *AND* $\hat{m}^{th}_k$*'s target maturity* $\geq m_{min})$ *OR* $(H^{C^I}_{k|k-1}(\hat{m}_k) \geq 1$ *AND* $g_{min} \leq g_{k|k-1}(\hat{m}_k) \leq g_{max})$ **then**

    Possible occluded target or association with clutter: Freeze and decrement maturity;

  end

  if $H^{C^I}_{k|k-1}(\hat{m}_k) \geq 1$ *AND* $g_{k|k-1}(\hat{m}_k) < g_{min}$ **then**

    Possible target survival: Unfreeze, increment maturity and associate the target with the $R^I_{k|k-1}(\hat{m}_k)^{th}$ measurement in Z_k;

  end

end

% Iterate over N_k measurements in Z_k:

for $n_k = 1, 2, \dots, N_k$ **do**

  if $H^{R^I}_{k|k-1}(n_k) == 0$ *OR* $mg_{k|k-1}(n_k) > g_{max}$ **then**

    Possible birth of a target: Initialise a new *xlstm* tuple with m_{min} maturity;

  end

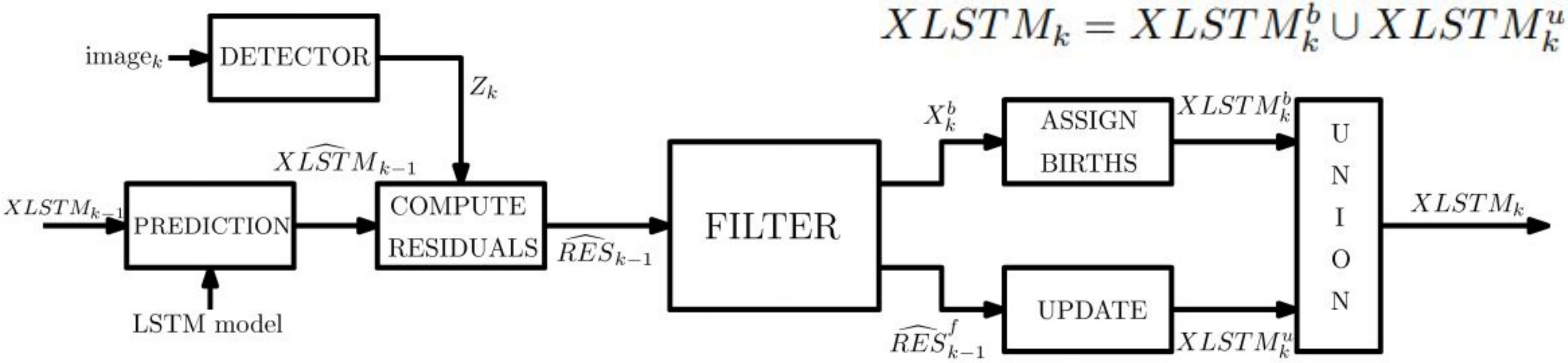
end

Algorithm 1: Data association algorithm.

Proposed algorithm: Complexity analysis

- A basic Hungarian Matching: $O(n^4)$
- GM-PHD filter: $O(M_{t-1} \times N_t)$
- The proposed method: $O(\max([M_{t-1}, N_t]))$

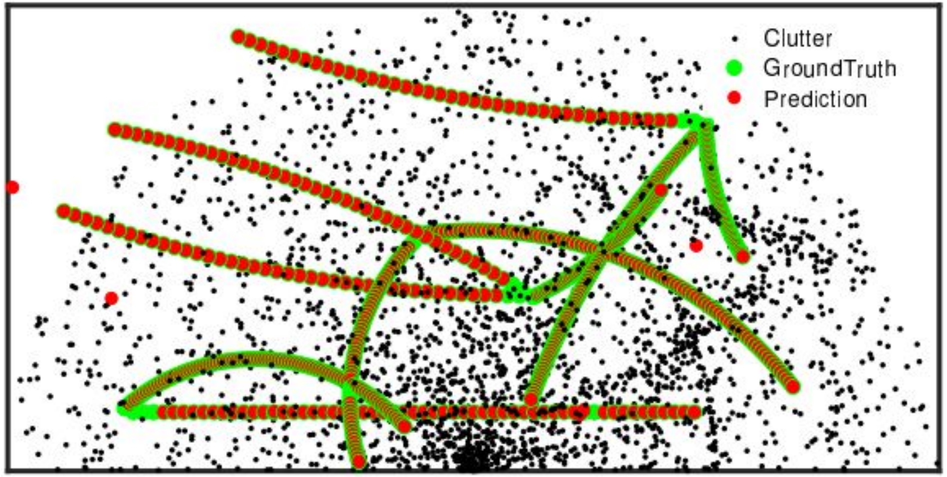
$$XLSTM_k = XLSTM_k^b \cup XLSTM_k^u$$



Experimental results

Multi-target filtering: experimental results

- The proposed algorithm is applied to a synthetic multi-target filtering scenario:
- Multiple scenarios are considered, such as:
  - Variable number of targets
  - Non-linear motion
  - Birth/spawn of targets
  - Dense random clutter with a Poisson distribution
  - Noisy measurement
  - Occlusion
  - Merge of targets



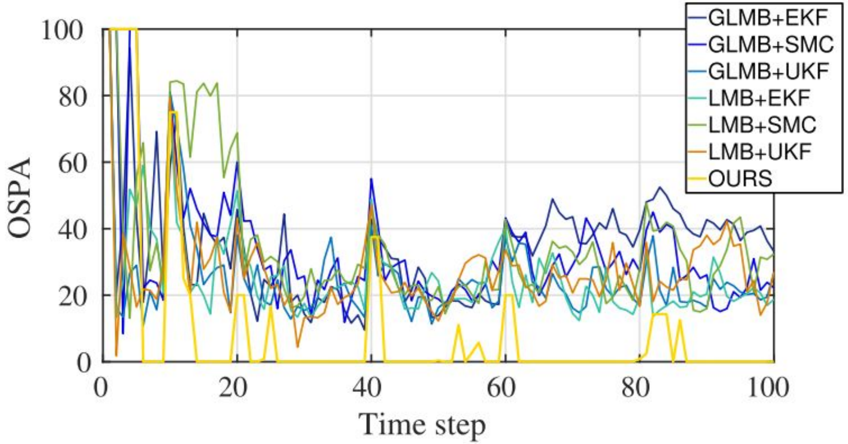
- Temporal overlay visualisation of the filtering result

Multi-target filtering: experimental results

Multi-target filtering: experimental results

- Optimal Sub-Pattern Assignment (OSPA) is used as the quantitative metric.

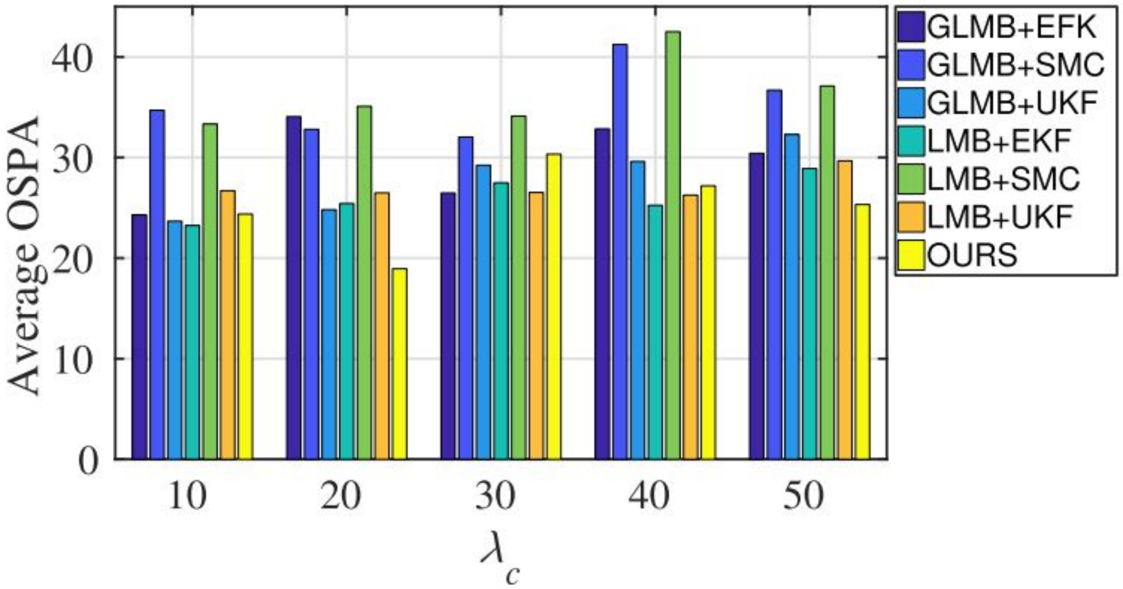
$$\mathrm{OSPA}(A,B) = \frac{1}{\max\{\alpha,\beta\}}\left(c^p|\alpha-\beta| + cost\right)^{1/p}$$



Algorithm	OSPA Card	OSPA Loc	OSPA
PHD-EKF	9.25 ± 15.44	20.86 ± 9.83	30.11 ± 14.82
PHD-SMC	12.76 ± 15.67	46.08 ± 17.36	58.84 ± 15.85
PHD-UKF	10.33 ± 18.17	19.73 ± 8.14	30.06 ± 16.21
CPHD-EKF	7.10 ± 14.91	23.00 ± 11.06	30.10 ± 16.16
CPHD-SMC	11.18 ± 13.72	46.08 ± 18.59	57.25 ± 17.72
CPHD-UKF	5.50 ± 14.79	22.39 ± 11.21	27.89 ± 15.43
LMB-EKF	4.59 ± 14.60	22.59 ± 8.60	27.18 ± 13.96
LMB-SMC	12.07 ± 19.75	23.47 ± 13.49	35.54 ± 17.95
LMB-UKF	$\mathbf{3.77 \pm 13.82}$	21.94 ± 10.22	25.72 ± 14.39
GLMB-EKF	6.37 ± 17.66	20.13 ± 8.02	26.50 ± 15.20
GLMB-SMC	6.11 ± 11.91	21.07 ± 6.78	27.19 ± 11.49
GLMB-UKF	11.79 ± 16.34	19.84 ± 9.75	31.63 ± 15.12
OURS	10.36 ± 13.25	$\mathbf{8.77 \pm 7.50}$	$\mathbf{19.12 \pm 14.39}$

Multi-target filtering: experimental results

- Robustness against clutter density:



Conclusions and future work

- An algorithm is proposed to address non-linearity and fixed motion model challenges of the available multi-target filtering algorithms.
- It is based on the use of a novel target tuple definition, LSTM architecture for motion modelling and a linearly complex data association step.
- Future work:
  - Real data
  - Other applications: tracking, detection, etc.
  - End to end implementation

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Thank you

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