MULTI-TARGET VISUAL TRACKING USING RANGOM FINITE SET-BASED FILTRES

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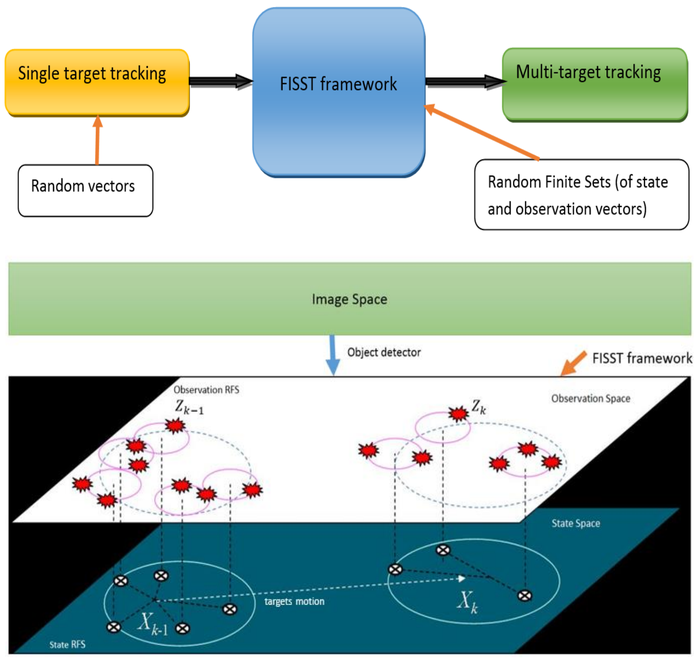
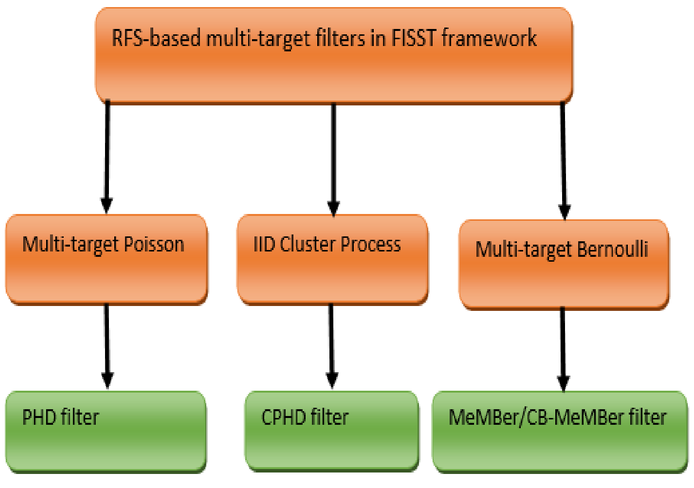
1. Abstract

A Multi-target visual tracking (MTVT) algorithm is developed using the recently popular Random finite set (RFS)-based filters. RFS is used to naturally represent the varying number of non-ordered multi-target states and observations which is analogous to random vector for single target tracking. Finite set statistics (FISST), the study of statistical properties of RFS, is the first systematic treatment of multi-sensor multi-target filtering as a unified Bayesian framework using random set theory.



2. RFS-based Filters

There are different types of RFS-based filters such as probability hypothesis density (PHD), cardinalized PHD (CPHD) and cardinality balanced multi-target multi-Bernoulli (CB-MeMBer) filters with the assumption of uncorrelated targets, and can be implemented using two different methods: Gaussian mixture (GM) and sequential Monte Carlo (SMC).

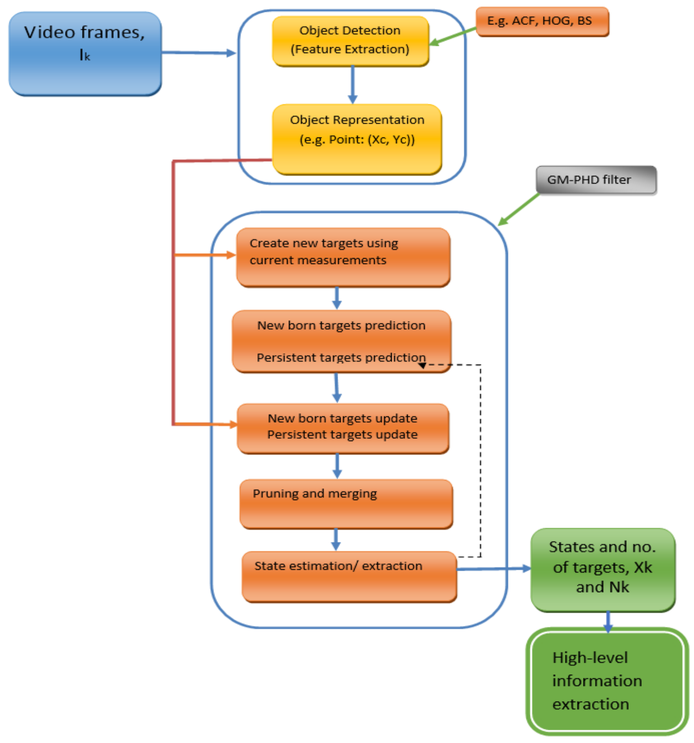


References

[1]. V. Ba-Ngu and M. Wing-Kin, The Gaussian Mixture Probability Hypothesis Density Filter, IEEE Trans. on Signal Processing, 2006.
[2]. B. Ristic, D.Clark, V. Ba-Ngu, and Vo. Ba-Tuong, Adaptive Target Birth Intensity for PHD and CPHD Filters, IEEE Transactions on Aerospace and Electronic Systems, 2012.
[3]. D. Piotr, A. Ron, P. Pietro, and P. Serge, Fast Feature Pyramids for Object Detection, IEEE Transactions on PAMI, 2014
[4]. B. Ristic, V. Ba-Ngu, D. Clark, V. Ba-Tuong, A Metric for Performance Evaluation of Multi-Target Tracking Algorithms, IEEE Transactions on Signal Processing, July 2011.

3. Procedures

Adaptive birth Gaussian mixture-based implementation of PHD (GM-PHD) filter [1], [2] with 3 different object detection algorithms such as background subtraction (BS) for only static camera, Histogram of oriented gradients (HOG) and aggregated channel features (ACF) [3] for both static and moving cameras is used to develop this MTVT algorithm. GM-PHD filter has linear complexity with the number of targets, and estimates both states and cardinality of targets (pedestrians in this case).



4. Results

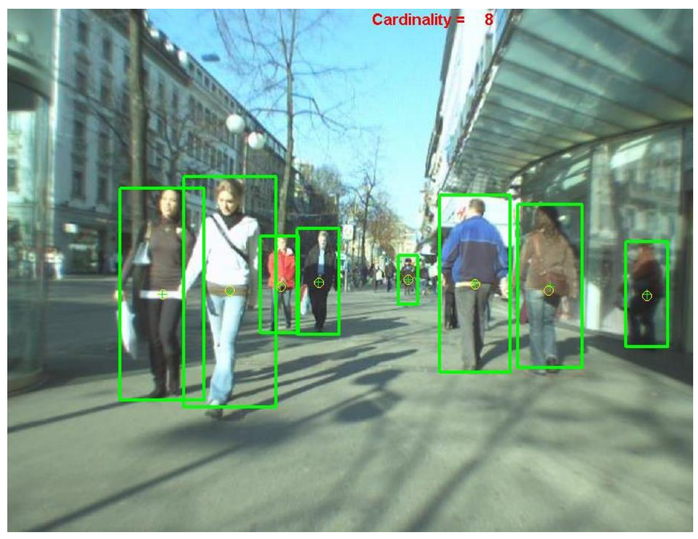
Sparsely populated video from static camera, PETS09 L1 data set, detection (green), tracking (yellow).

Medium populated video from static camera, PETS09 L2 data set, detection (green), tracking (yellow).

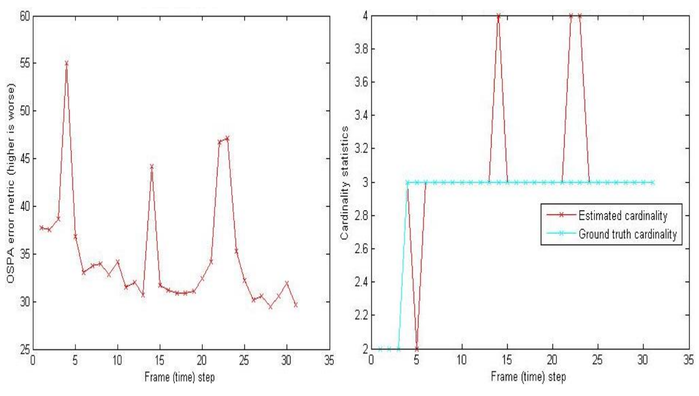
5. Results (Continued)

Densely populated video from static camera, PETS09 L3 data set, detection (green), tracking (yellow)..

Medium populated video from moving camera ETH data set, detection (green), tracking (yellow).



Performance using optimal Sub-pattern assignment (OSPA) metric [4] is given below for 30 frames. The overall OSPA error of the developed MTVT over 795 frames of PETS09 L1 data set is 30.94 which is lower than the traditional tracking algorithm, 42.4, and it also takes less time.



6. Conclusion

RFS-based filters are a principled and mathematically well-formulated multi-target filters that directly extend single-target to multi-target tracking using FISST technique in a Bayesian framework. MTVT algorithm using measurement-driven GM-PHD filter using ACF detection algorithm is developed, and is evaluated using OSPA metric.

Acknowledgement

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