Efficient Diverse Ensemble for Discriminative Co-Tracking

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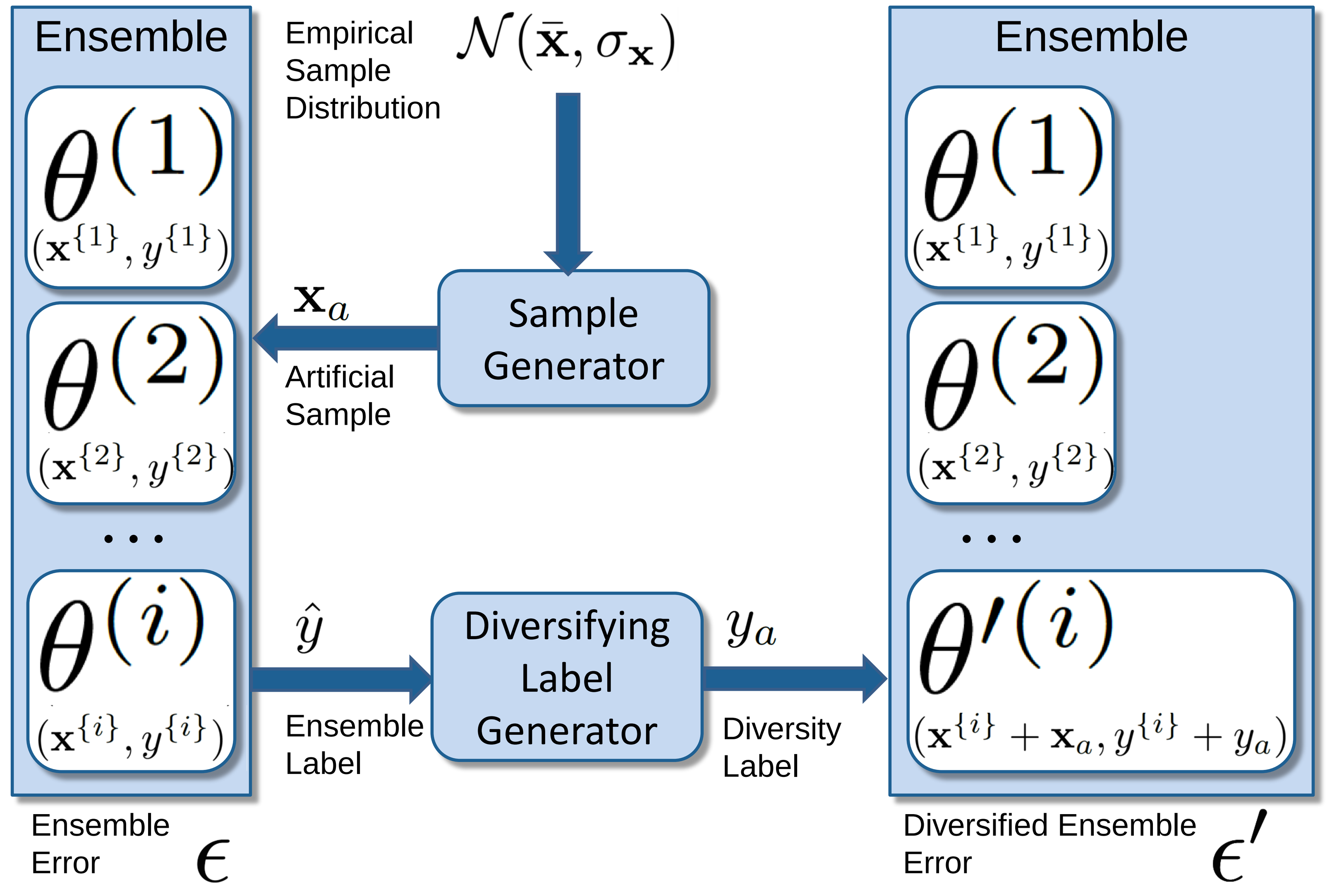
Abstract

Addressed challenges of ensemble discriminative tracking:

Creation	Random subsets of negative samples
Diversity	Generating effective artificial samples
Stability-Plasticity	Dual memory + query optimization
Model Drift	Online bagging + artificial samples

Promoting Diversity

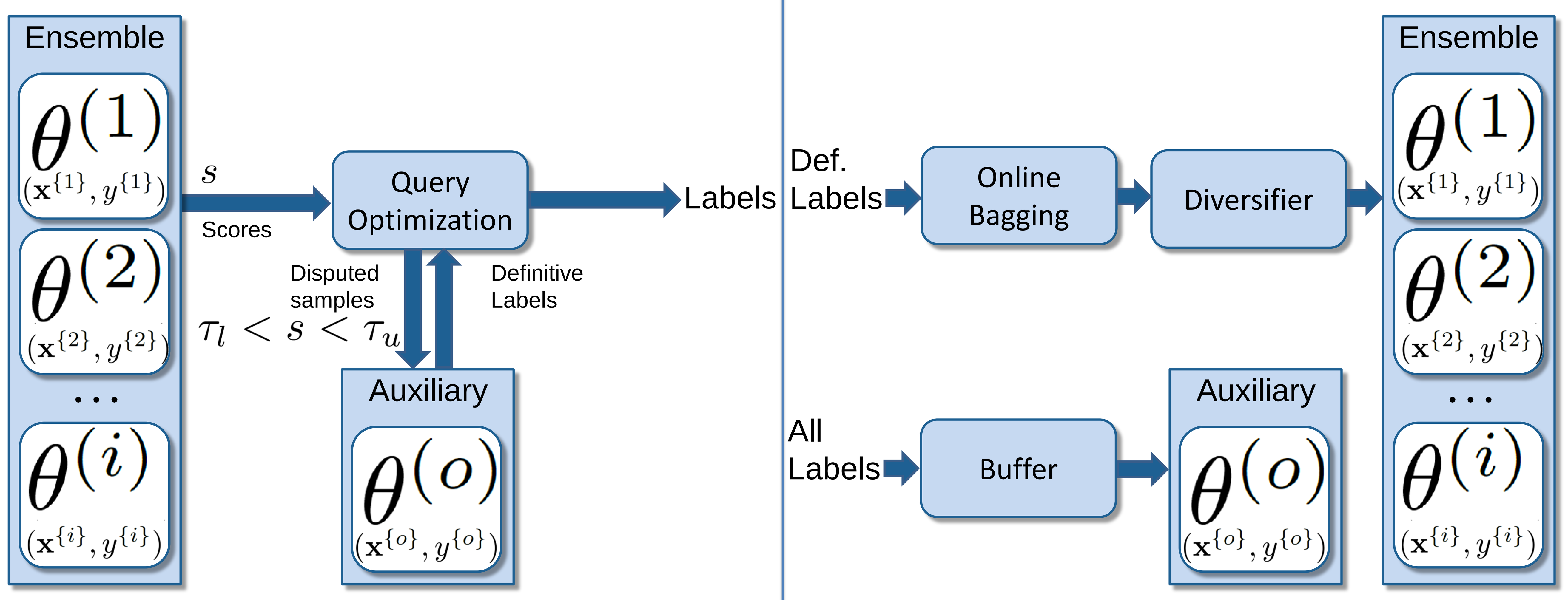


Here, $\theta'^{(i)}$ is a diversified classifier, because it has a set of diversity samples with labels that is intentionally set to oppose the ensemble label. If $\epsilon' \leq \epsilon$ then the update is accepted.

Tracker Concept

COLLABORATIVE CLASSIFICTION

UPDATE



BENEFITS OF ACTIVE CO-TRAINING

Using active learning to select which samples to query from long-memory auxiliary classifier, based on the uncertainty metric

- ✓ Gaining generalization and speed-up by querying only the most informative samples from the long-memory complex classifier
- ✓ Balances between long and short term memory automatically
- ✓ Reduce label classification uncertainty
- ✓ Breaks self learning loop

TRACKER PROPERTIES

- ✓ Accurate (Comparable with state-of-the-art)
- ✓ Reliable (Graceful degradation)
- ✓ Real-time Processing (~ 22 fps)
- ✓ Robust (High performance under various challenges)
- ✓ Compatible with Embedded Systems

References:
[1] K. Meshgi, S. Oba, and S. Ishii, Robust Discriminative Tracking via Query-by-Bagging, AVSS'16.
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[3] A. Lapedriza, H. Pirsiavash, Z. Bylinskii, and A. Torralba. Are all training examples equally valuable? arXiv, 2013
[4] A. Krogh, J. Vedelsby, et al. Neural network ensembles, cross validation, and active learning. NIPS'95.
[5] F. Tang, S. Brennan, Q. Zhao, and H. Tao. Co-tracking using semi-supervised support vector machines. ICCV'07
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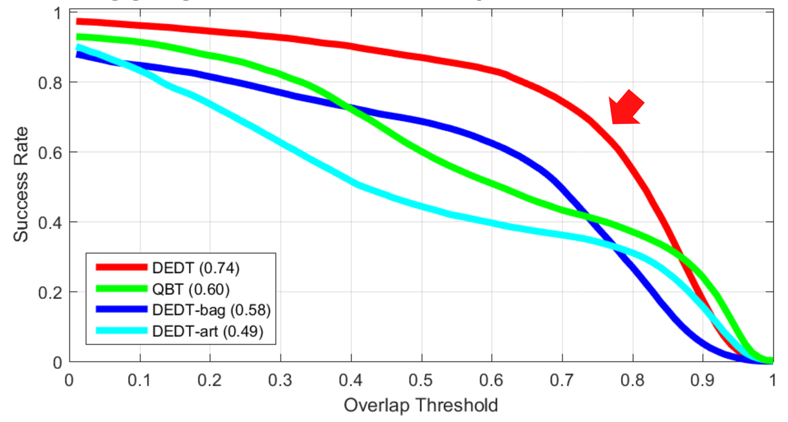
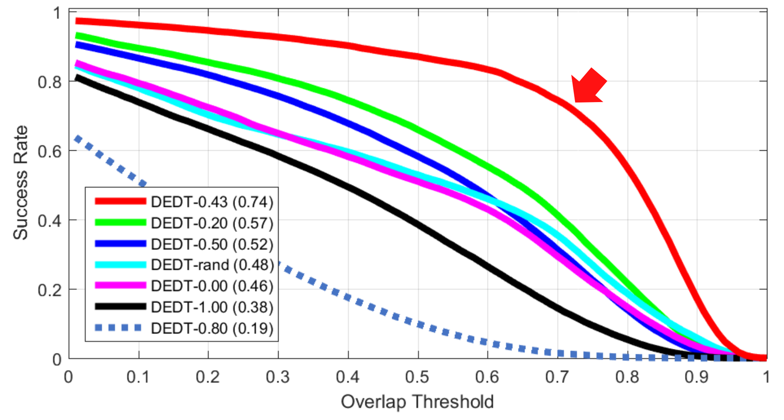
Results

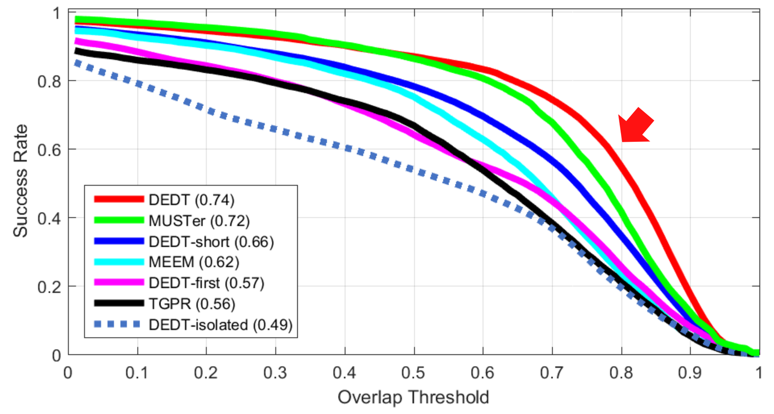
The effect of different update schemes: bagging, artificial diversity data, both.



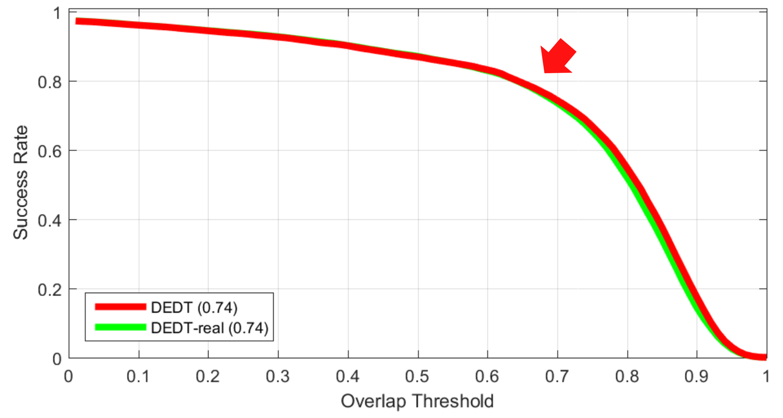
The effect of the "activeness" parameter, balancing stability-plasticity equilibrium.



The effect of dual memory schemes: ensembles with no update, no data exchange, and no long-term memory have inferior performance.



Using artificial data (compared to real data with similar data dist.) does not degrade the performance of the tracker.



VOT 2015:

	STRK	TGPR	MEEM	STPL	CMT	SRDCF	CCOT	Ours
Accuracy	0.47	0.48	0.50	0.53	0.49	0.56	0.54	0.58
Robustness	1.26	2.31	1.85	1.35	1.81	1.24	0.82	1.36

OTB-100:

	TLD	STRK	MEEM	STPL	CMT	SRDCF	CCOT	Ours
Avg. Succ	0.46	0.48	0.65	0.62	0.63	0.64	0.74	0.69
Avg. Prec	0.58	0.59	0.62	0.73	0.74	0.71	0.85	0.81
$IoU > 0.5$	0.52	0.52	0.62	0.71	0.72	0.75	0.88	0.78

OTB-50:

Attribute	TLD	STRK	TGPR	MEEM	MSTR	STPL	CMT	SRDCF	CCOT	Ours
IV	0.48	0.53	0.54	0.62	0.73	0.68	0.73	0.70	0.75	0.75
DEF	0.38	0.51	0.61	0.62	0.69	0.70	0.69	0.67	0.69	0.69
OCC	0.46	0.50	0.51	0.61	0.69	0.69	0.69	0.70	0.76	0.72
SV	0.49	0.51	0.50	0.58	0.71	0.68	0.72	0.71	0.76	0.74
IPR	0.50	0.54	0.56	0.58	0.69	0.69	0.74	0.70	0.72	0.73
OPR	0.48	0.53	0.54	0.62	0.70	0.67	0.73	0.69	0.74	0.74
OV	0.54	0.52	0.44	0.68	0.73	0.62	0.71	0.66	0.79	0.76
LR	0.36	0.33	0.38	0.43	0.50	0.47	0.55	0.58	0.70	0.58
BC	0.39	0.52	0.57	0.67	0.72	0.67	0.69	0.70	0.70	0.73
FM	0.45	0.52	0.46	0.65	0.65	0.56	0.70	0.63	0.72	0.74
MB	0.41	0.47	0.44	0.63	0.65	0.61	0.65	0.69	0.72	0.72
Avg. Succ	0.49	0.55	0.56	0.62	0.72	0.69	0.72	0.70	0.75	0.74
Avg. Prec	0.60	0.66	0.68	0.74	0.82	0.76	0.83	0.78	0.84	0.84
$IoU > 0.5$	0.59	0.64	0.66	0.75	0.86	0.82	0.83	0.83	0.90	0.89
Avg FPS	21.2	11.3	3.7	14.2	8.3	48.1	21.9	4.3	0.2	21.9