SportMamba: Adaptive Non-Linear Multi-Object Tracking with State Space Models for Team Sports

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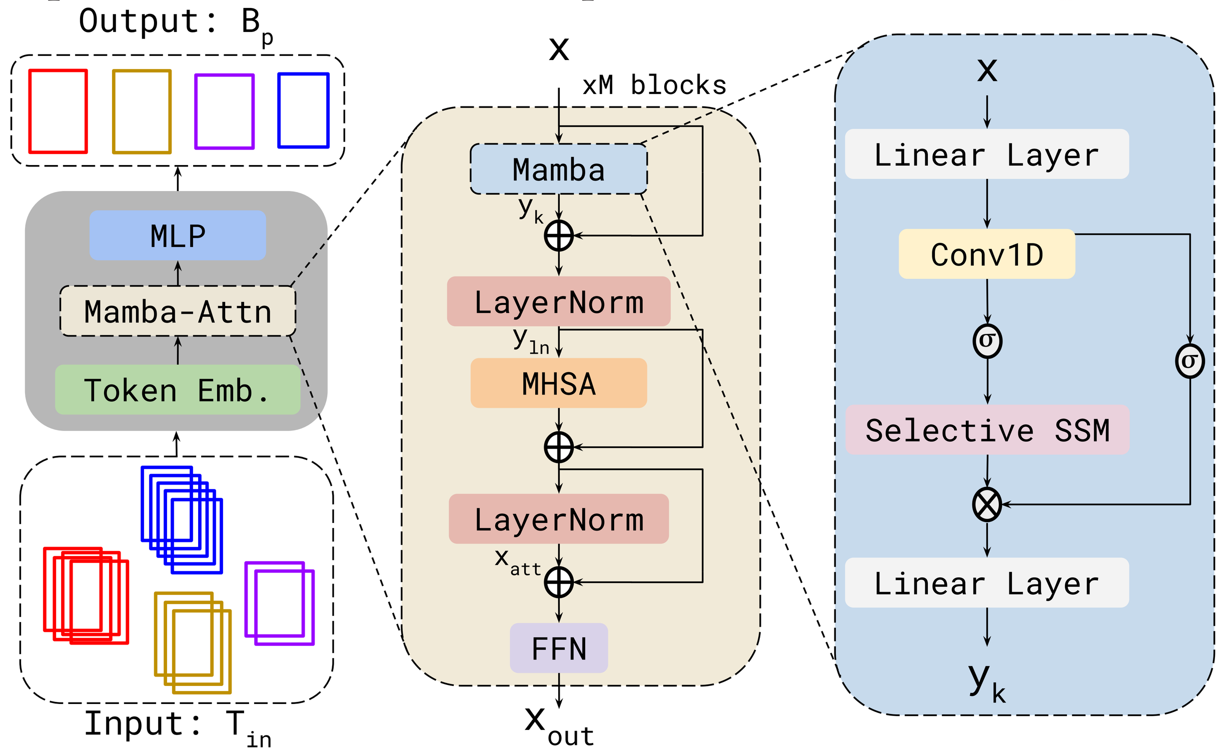
Key Contributions

- **SportMamba:** A hybrid online tracker designed for fast, non-linear motion in sports.
- **Motion Model:** Integrates Mamba state-space and self-attention for accurate motion prediction.
- **Spatial Matching:** Uses height-adaptive IoU and buffered association for robust tracking.
- **Performance:** Achieves SOTA on SportsMOT and strong zero-shot generalization to VIP-HTD.

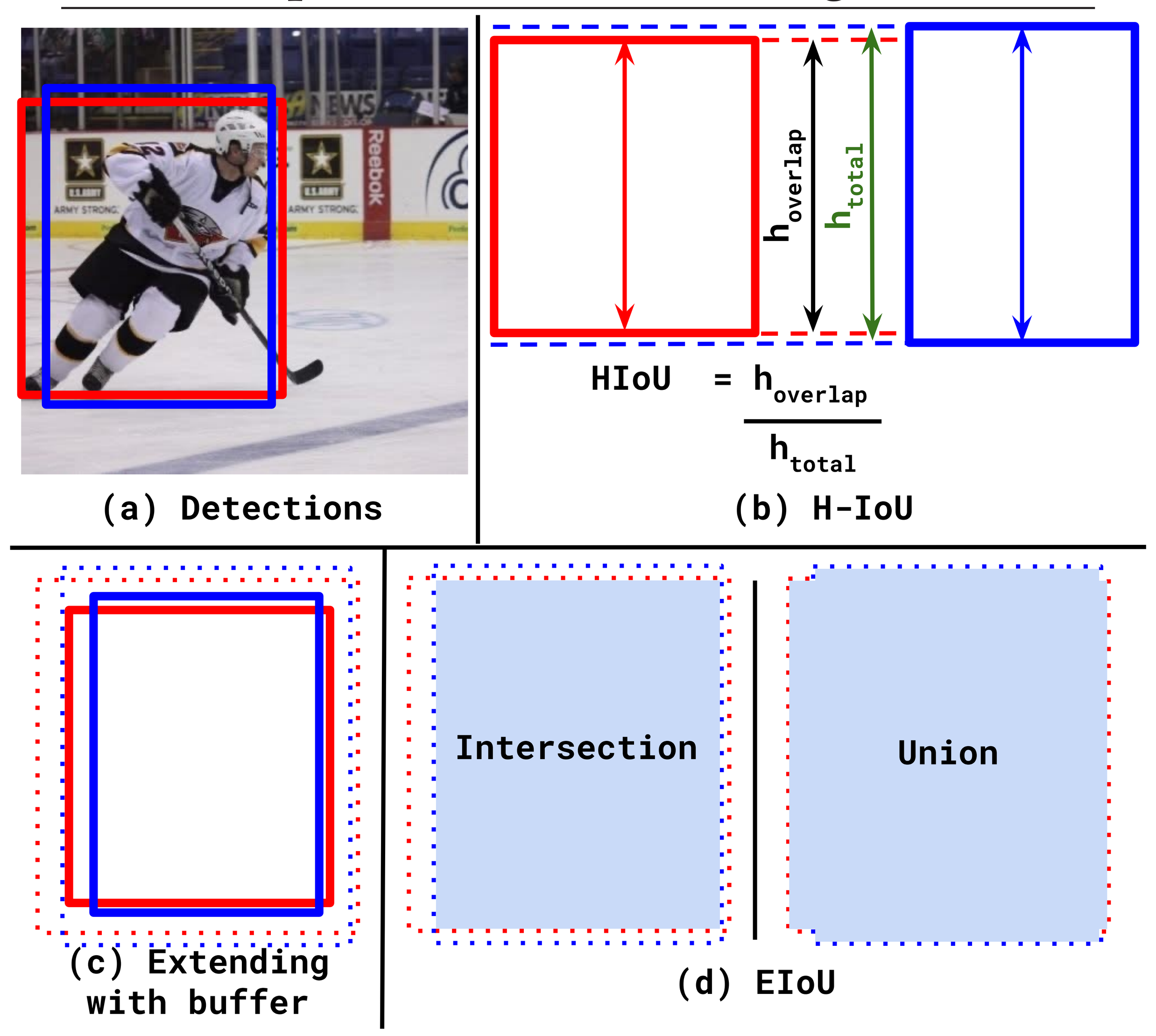
Motion Model

Token embeddings encode past trajectories, which are processed through Mamba-Attention blocks and MHSA to capture long-range motion dependencies. This representation is passed to an MLP head to predict future bounding boxes.



Spatial Matching

Visual Representation of HIoU against EIoU

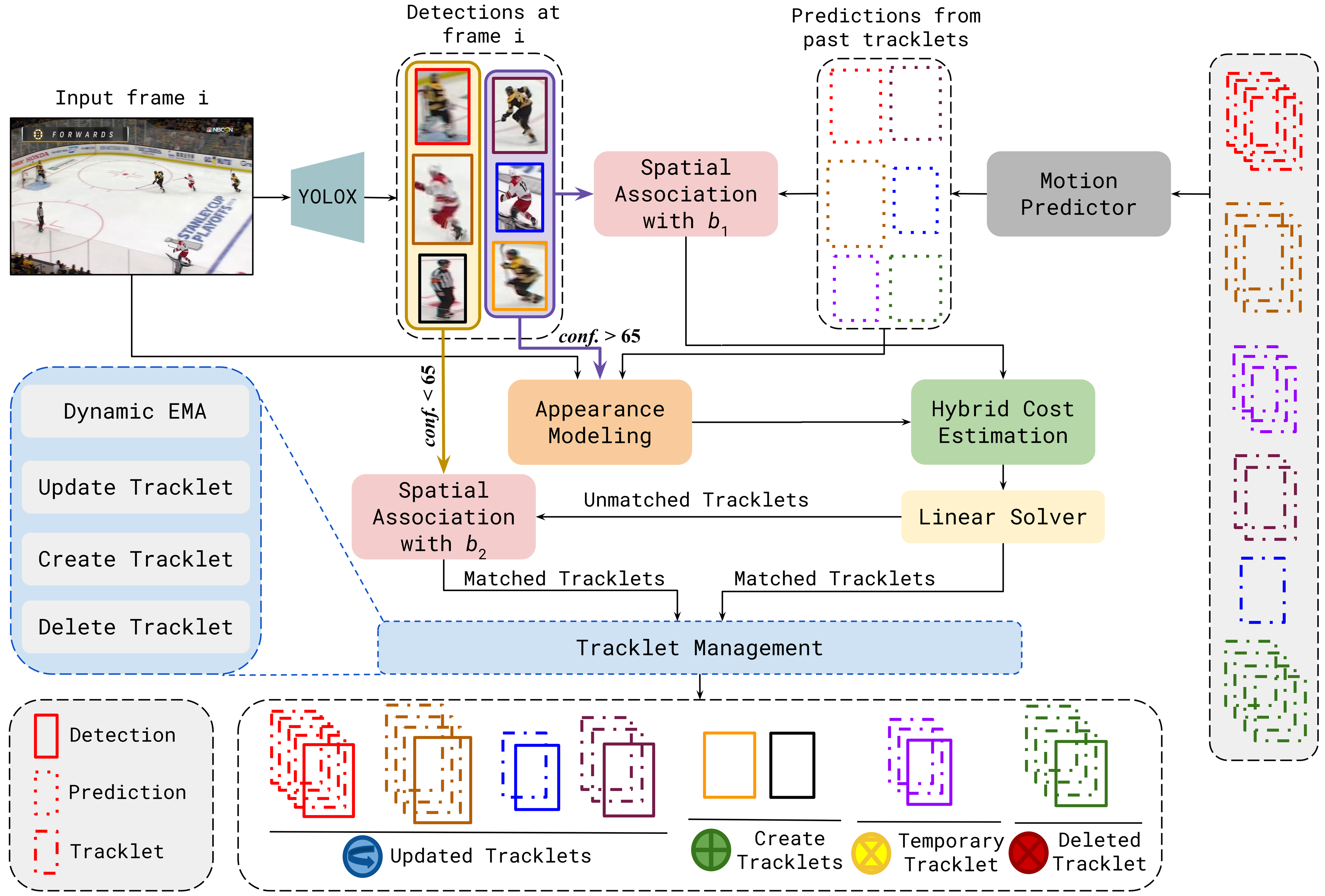


Spatial association is done using Height-Adaptive EIoU (HA-EIoU) defined as:

$$\text{HA-EIoU} = \text{HIoU}.\text{EIoU} \tag{1}$$

SportMamba

Motivation:
Tracking players in team sports is extremely challenging due to fast, non-linear motion, frequent occlusions, and similar appearances (e.g., jerseys). Traditional Kalman Filter-based or appearance-only trackers **struggle in these settings**. While transformer-based models offer better modeling, they are often too heavy for real-time use.



Method:

1. **Fine-tuned Detector:** Identifies players in each frame.
2. **Motion Predictor:** Forecasts future positions using past trajectories.
3. **High-Confidence Matching:** Uses appearance features and height-adaptive IoU for robust associations.
4. **Fallback Matching:** Applies relaxed IoU when appearance cues are unreliable.
5. **Tracklet Management:** Creates, updates, deletes tracklets and updates features via dynamic EMA.

Qualitative Results

Hybrid Cost Estimation

The hybrid cost matrix is estimated as a weighted sum of appearance and spatial similarity, defined as:

$$\begin{aligned}\mathcal{J}_f &= \lambda_{reid}\mathcal{J}_{reid} + \lambda_{ssim}\mathcal{J}_{ssim}\\ \mathcal{J}_f &= \lambda_{reid}(1 - S_{reid}) + \lambda_{ssim}(1 - \text{HA-EIoU})\end{aligned} \tag{2}$$

where,

$$S_{reid}(i,j) = \frac{e_i^T \cdot e_j^D}{\|e_i^T\|\|e_j^D\|} \tag{3}$$

Loss Functions

The overall objective function for the motion predictor:

$$\mathcal{L} = \lambda_{l1}^s \mathcal{L}_{L1}^s + \lambda_{ciou}\mathcal{L}_{ciou} \tag{4}$$

where,

$$\mathcal{L}_{L1}^s = \begin{cases}\frac{1}{2}(P_t - G_t)^2, & \text{if } |P_t - G_t| < 1,\\ |P_t - G_t| - \frac{1}{2}, & \text{otherwise.}\end{cases} \tag{5}$$

Quantitative Results

Tracking results for SportsMOT test set

Method	HOTA↑	IDF1↑	AssA↑	MOTA↑	DetA↑
Filter-based Methods					
ByteTrack	62.8	69.8	51.2	94.1	77.1
OC-SORT	71.9	72.2	59.8	94.5	86.4
*OC-SORT	73.7	74.0	61.5	96.5	88.5
Learning-based Methods					
DiffMOT	72.1	72.8	60.5	94.5	86.0
*ByteSSM	74.4	74.5	62.4	96.8	88.8
Ours	77.3	77.7	66.8	96.9	89.5

Zero-shot Tracking results for VIP-HTD test set

Method	HOTA↑	IDF1↑	AssA↑	MOTA↑	DetA↑
Filter-based Methods					
ByteTrack	64.4	81.1	64.8	73.9	64.2
OC-SORT	61.0	75.4	58.9	74.6	63.4
Deep OC-SORT	59.4	73.4	56.1	74.5	56.1
Learning-based Methods					
DiffMOT	64.1	79.4	63.6	76.1	65.0
ByteSSM	63.4	77.7	61.8	76.2	65.4
Ours	65.1	80.1	64.6	76.2	65.9

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