STRIKE: A Framework for Smoothing High-Impact Martial Arts Motion

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***Abstract*—This work investigates the use of the Unscented Kalman Filter (UKF) to improve the accuracy and temporal consistency of joint detection in Muay Thai videos processed on edge devices. By applying the UKF to noisy keypoints estimated by lightweight YOLO-based pose detectors, we observe reduced mean per joint position error (MPJPE) on benchmark datasets, particularly in sequences where motion is smooth but detection jitter is significant. Our method demonstrates that fusing temporal dynamics with lightweight detection improves pose stability on resource-constrained devices, enabling practical applications such as automated scoring and referee assistance in combat sports.**

***Index Terms*—Pose Estimation, Unscented Kalman Filter, Computer Vision, Sports Analytics, Muay Thai, Edge Computing**

I. INTRODUCTION

In this paper, we introduce the STRIKE (Smoothed Tracking & Recognition of In-fight Kinetic Engagement) framework, designed to enhance motion analysis in martial arts. Real-time human pose estimation plays an increasingly important role in sports analytics, training feedback, and referee support systems [9], [11]. In martial arts disciplines like Muay Thai, characterized by rapid, high-impact strikes and complex defensive maneuvers, accurate joint tracking is essential for an objective evaluation of technique. Deploying such systems on edge devices is attractive for in-situ analysis but typically requires lightweight pose estimation models [7], [8], which often produce noisy or incomplete detections, particularly under fast motion, occlusion, or suboptimal lighting.

This paper explores how temporal filtering, specifically the Unscented Kalman Filter (UKF), can reduce detection noise while remaining computationally efficient. By leveraging the kinematic continuity of human motion, the UKF smooths predictions from YOLO-based detectors, yielding trajectories that better reflect the true underlying motion.

II. BACKGROUND

Recent years have seen significant progress in multimodal and sensor-based human action recognition [2], [3], [6]. Techniques like hybrid deep learning [1] and multi-sensor fusion [7], [8] achieve robust performance by integrating diverse data streams. Advances in detailed action understanding have pushed the boundaries of what can be inferred from motion [12]. However, vision-only systems remain appealing for simplicity and lower deployment cost [10], [11].

In the context of combat sports, research such as [4] highlights the challenge of noisy labels and fast, complex motion, which degrades frame-wise pose detection accuracy. Prior works often address this with computationally heavy spatiotemporal networks [10], but these are unsuitable for edge devices. Our approach differs by coupling a lightweight detector with a classic, efficient Bayesian filter. The UKF extends the standard Kalman Filter (KF) and Extended Kalman Filter (EKF) by better handling the non-linearities inherent in human motion without requiring analytic Jacobians.

III. METHODOLOGY

We propose a two-stage pipeline. First, we extract 2D joint positions frame by frame using a lightweight YOLO-based pose estimator [13]. Then, we apply a separate Unscented Kalman Filter per joint to exploit temporal coherence.

The UKF maintains a state vector $x = [x, y, v, \theta, \omega]^T$, where (x, y) are joint positions, v is velocity, θ is heading, and ω is turn rate, operating in a predict-update cycle as summarized in Algorithm 1.

A. Mathematical Formulation of the UKF

The Unscented Kalman Filter (UKF) for each joint estimates the state vector

$$\mathbf{x} = \begin{bmatrix} x \\ y \\ v \\ \theta \\ \omega \end{bmatrix} \tag{1}$$

where (x, y) is the 2D joint position, v is velocity, θ is heading, and ω is turn rate.

Given the prior mean and covariance $(\mathbf{x}_{k-1}, \mathbf{P}_{k-1})$, the UKF proceeds as:

1) Generate $2n + 1$ sigma points:

$$\chi_0 = \mathbf{x}_{k-1} \tag{2}$$

$$\chi_i = \mathbf{x}_{k-1} + [\sqrt{(n+\lambda)\mathbf{P}_{k-1}}]_i, \quad i = 1, \ldots n \tag{3}$$

$$\chi_{i+n} = \mathbf{x}_{k-1} - [\sqrt{(n+\lambda)\mathbf{P}_{k-1}}]_i, \quad i = 1, \ldots n \tag{4}$$

with $\lambda = \alpha^2(n + \kappa) - n$.

2) Predict each sigma point by the nonlinear motion model:

$$x_k = x_{k-1} + \frac{v_{k-1}}{\omega_{k-1}} \left(\sin(\theta_{k-1} + \omega_{k-1}\Delta t) - \sin(\theta_{k-1})\right) \tag{5}$$

$$y_k = y_{k-1} - \frac{v_{k-1}}{\omega_{k-1}} \left(\cos(\theta_{k-1} + \omega_{k-1}\Delta t) - \cos(\theta_{k-1})\right) \tag{6}$$

For small $|\omega|$, use the linear approximation:

$$x_k \approx x_{k-1} + v_{k-1}\Delta t \cos(\theta_{k-1}) \tag{7}$$

$$y_k \approx y_{k-1} + v_{k-1}\Delta t \sin(\theta_{k-1}) \tag{8}$$

3) Reconstruct predicted mean and covariance:

$$\hat{\mathbf{x}}^- = \sum_{i=0}^{2n} W_m^{[i]} \chi_i^- \tag{9}$$

$$\mathbf{P}^- = \sum_{i=0}^{2n} W_c^{[i]} (\chi_i^- - \hat{\mathbf{x}}^-)(\chi_i^- - \hat{\mathbf{x}}^-)^T + \mathbf{Q} \tag{10}$$

4) Update: transform predicted sigma points with the measurement model $h(\cdot)$ (extracting (x, y)):

$$\gamma_i = h(\chi_i^-) = [x, y]^T \tag{11}$$

$$\hat{\mathbf{z}} = \sum_{i=0}^{2n} W_m^{[i]} \gamma_i \tag{12}$$

$$\mathbf{S} = \sum_{i=0}^{2n} W_c^{[i]} (\gamma_i - \hat{\mathbf{z}})(\gamma_i - \hat{\mathbf{z}})^T + \mathbf{R} \tag{13}$$

The cross-covariance and Kalman gain:

$$\mathbf{T} = \sum_{i=0}^{2n} W_c^{[i]} (\chi_i^- - \hat{\mathbf{x}}^-)(\gamma_i - \hat{\mathbf{z}})^T \tag{14}$$

$$\mathbf{K} = \mathbf{T}\mathbf{S}^{-1} \tag{15}$$

Apply the update:

$$\hat{\mathbf{x}}_k = \hat{\mathbf{x}}_k^- + \mathbf{K}(\mathbf{z}_k - \hat{\mathbf{z}}_k) \tag{16}$$

$$\mathbf{P}_k = \mathbf{P}_k^- - \mathbf{K}\mathbf{S}_k\mathbf{K}^T \tag{17}$$

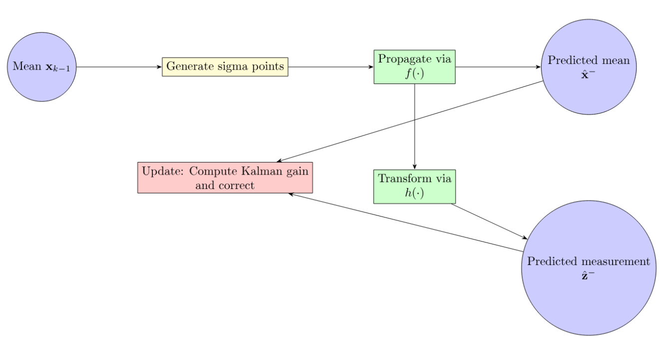

Fig. 1. The Unscented Kalman Filter Process Flow. Sigma points are propagated through the motion model and the measurement model to estimate refined joint trajectories.

Algorithm 1 Pose Tracking with YOLO and Unscented Kalman Filter

Require: Video Frame Sequence $V = \{v_1, v_2, ..., v_N\}$
Require: UKF Process Noise Q, Measurement Noise R
Ensure: Filtered Keypoint Sequence $\hat{\mathbf{X}} = \{\hat{\mathbf{x}}_1, \hat{\mathbf{x}}_2, ..., \hat{\mathbf{x}}_N\}$
Initialize UKF for each joint $j \in \{1, ..., J\}$: $\mathcal{F} = \{\text{UKF}_1, ..., \text{UKF}_J\}$
Run YOLO on v_1 to get initial keypoints $\mathbf{z}_1$
for each joint $j = 1$ to J **do**
  Initialize $\hat{\mathbf{x}}_{1|1,j}$ and $P_{1|1,j}$ with $\mathbf{z}_{1,j}$
end for
Store $\hat{\mathbf{X}}_1 \leftarrow \{\hat{\mathbf{x}}_{1|1,1}, ..., \hat{\mathbf{x}}_{1|1,J}\}$
for $k = 2$ to N **do**
  Run YOLO on v_k to get keypoints $\mathbf{z}_k$
  if person detected in v_k **then**
    for each joint $j = 1$ to J **do**
      Predict: $\hat{\mathbf{x}}_{k|k-1,j}$, $P_{k|k-1,j}$ with $f(\cdot)$ and Q
      Update: $\hat{\mathbf{x}}_{k|k,j}$, $P_{k|k,j}$ with $\mathbf{z}_{k,j}$, $h(\cdot)$, R
    end for
  else
    for each joint $j = 1$ to J **do**
      Predict only
    end for
  end if
  Store $\hat{\mathbf{X}}_k$
end for
return $\hat{\mathbf{X}}$ =0

IV. EXPERIMENTS AND RESULTS

A. Parameter Tuning for Filtering

For the Penn Action benchmark, we used:

- **Time step:** $dt_{\text{ukf}} = 1.0/\text{fps}$, where fps is from annotations or defaults to 60.
- **Process noise:** $q_{\text{pos}} = 1.5$, $q_{\text{vel}} = 2.0$, $q_{\text{turn}} = 2.5$, $Q = \text{diag}(q_{\text{pos}}, q_{\text{pos}}, q_{\text{vel}}^2, 0, q_{\text{turn}}^2)$.
- **Measurement noise:** $r_{\text{val}} = 89.3$, $R = r_{\text{val}} \cdot I_2$.

For real-world video, process-noise is increased ($q_{\text{pos}} = 9.0$, $q_{\text{vel}} = 11.0$, $q_{\text{turn}} = 13.0$) to adapt to unpredictable movements.

B. Evaluation Metrics: MPJPE and F1-Score

Mean per joint position error (MPJPE) and F1-Score are computed as:

$$\text{MPJPE} = \frac{1}{NF} \sum_{f=1}^{F} \sum_{n=1}^{N} \left\| \hat{\mathbf{p}}_{f,n} - \mathbf{p}_{f,n}^{\text{GT}} \right\|_2 \tag{18}$$

$$\text{Precision} = \frac{TP}{TP + FP} \tag{19}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{20}$$

$$\text{F1} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \tag{21}$$

where TP, FP, FN count visible joint detections with acceptable pixel error.

C. Penn Action Benchmark Results

TABLE I
OVERALL STATISTICS FOR UKF FILTERING ON PENN ACTION DATASET

Metric	Value
Total Sequences Processed	2326
Mean Raw YOLO MPJPE (pixels)	76.06
Mean Filtered MPJPE (pixels)	75.37
Accuracy Improvement (%)	0.91
Mean F1-Score Raw YOLO	0.4280
Mean F1-Score UKF	0.4221

TABLE II
SEQUENCES IMPROVED BY UKF

Metric	Value
Sequences Improved MPJPE	1135 of 2326 (48.8%)
Avg. MPJPE Improvement (in improved)	2.35%
Sequences Improved F1	747 of 2326 (32.1%)
Avg. F1 Improvement (in improved)	6.91%

TABLE III
TOP 10 SEQUENCES BY MPJPE IMPROVEMENT

Sequence ID	Raw MPJPE	Filtered MPJPE	MPJPE Impr. (%)
2239	170.73	13.13	92.31
2060	230.27	71.25	69.06
2001	32.84	10.77	67.20
1454	147.33	55.96	62.02
1459	189.00	84.02	55.54
1492	159.17	99.30	37.61
0434	221.19	139.25	37.05
0246	28.81	18.78	34.81
2240	163.87	110.89	32.33
0544	62.17	43.43	30.14

TABLE IV
TOP 10 SEQUENCES BY F1-SCORE IMPROVEMENT

Sequence ID	Raw F1	Filtered F1	F1 Impr. (%)
1542	0.0139	0.0643	362.59
0373	0.0543	0.2255	315.29
1821	0.0057	0.0183	221.05
1934	0.0276	0.0719	160.51
0374	0.0134	0.0301	124.63
1802	0.0210	0.0449	113.81
1459	0.2313	0.4825	108.60
1461	0.0137	0.0253	84.67
1544	0.0122	0.0213	74.59
1557	0.2722	0.4691	72.34

D. Real-World Benchmark and Hardware

Real-World Benchmark: To demonstrate practical feasibility, the full pipeline was run on a Muay Thai video (9,160 frames). Inference and filtering finished in 4 minutes and 30.3 seconds on consumer hardware: RTX3060 Galax 12GB GPU, Ryzen 5 2600 CPU, and 32GB (2x16GB) PuSkill Blade RAM at 2666MHz. This showcases near real-time speed and edge device suitability.

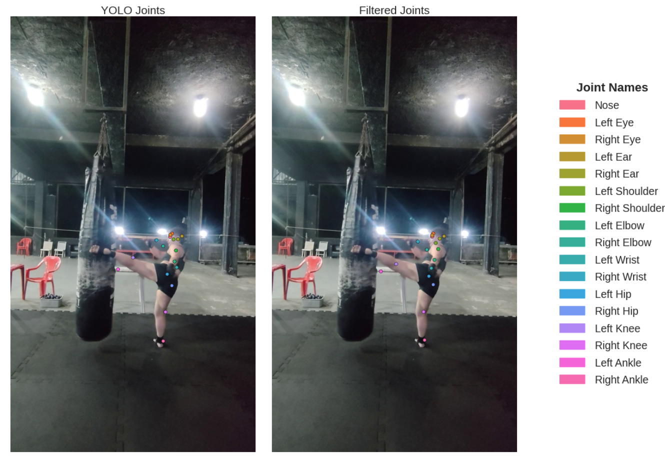

Fig. 2. Example filtering on a real-world Muay Thai training video. Left: YOLO keypoints (raw), Right: UKF-smoothed keypoints. The filter reduces temporal jitter and creates more plausible joint trajectories, especially on striking limbs and upper body.

E. Limitations

While the UKF improves performance on average, performance can decline for short, ballistic motions (e.g., kicks) due to the limitations of the "constant turn rate and velocity" state model.

V. CONCLUSION

This study demonstrates that lightweight temporal filtering with the Unscented Kalman Filter (UKF) is an efficient strategy to enhance pose tracking reliability on YOLO-based systems for edge devices. The UKF harnesses temporal continuity to reduce jitter and improve accuracy, especially in sequences affected by detection noise, while running efficiently on consumer hardware.

Despite some limitations for brief, high-acceleration movements, the method offers a practical balance between performance and computational cost. Future work will explore richer dynamical models, extend the framework for more challenging scenarios in martial arts analytics, and include testing in real time on edge devices.

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