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Poster

Reducing Motion Jitter in Monocular Motion Capture Data

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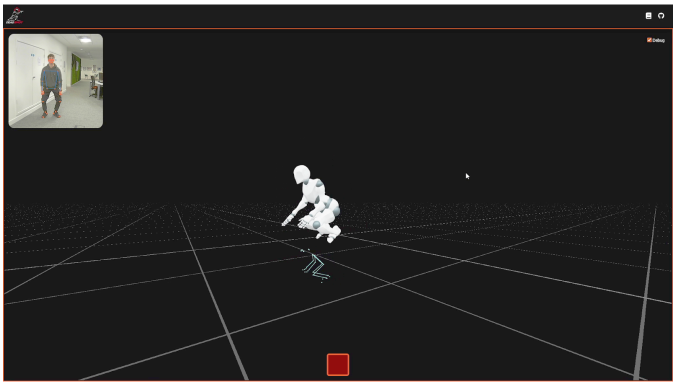

Figure 1: *Deadshot Application*

Abstract

We present Adaptive Velocity-Confidence Smoothing, a novel variation of the One Euro Filter and Confidence Weighted Filtering, primarily used to reduce noise in monocular-based pose estimation. This advancement addresses well-known limitations of existing temporal smoothing methods and demonstrates our alternative. We have applied this technique to our web-based motion capture tool, Deadshot [Hos25].

CCS Concepts

• ***Applied computing*** $\rightarrow$ ***Media arts;*** • ***Software and its engineering*** $\rightarrow$ ***Open source model;***

1. Introduction

Markerless motion-capture methods have emerged through advances in pose estimation. A key variant is monocular motion capture, which reconstructs motion from a single video input rather than a multi-camera setup. Compared with traditional multi-camera triangulation [MKT*20], monocular motion capture has a major limitation: accurately recovering 3D joint positions. AI frameworks such as MediaPipe BlazePose provide 2D coordinates (x, y), an estimated depth value (z), and confidence scores (c) for each joint [Goo26].

2. Estimated Jitter and Noise Reduction Algorithms

Pose-estimation models analyse image pixels to infer key joint landmarks. Because video input is noisy and some poses are ambiguous, landmark predictions can jitter over time, producing unstable motion that requires temporal smoothing.

Noise-reduction methods predate modern motion-capture pipelines and are widely used in signal and video denoising. Two commonly used approaches are the One Euro Filter and Confidence Weighted Filtering:

2.1. One Euro Filter

The One Euro Filter is a low-pass filtering algorithm for removing high-frequency noise in tracking systems [CRV12]. It uses the derivative of data points to compute a smoothing coefficient. The smaller the change, the stronger the smoothing.

The main limitation of the One Euro Filter is that intentional jitter, such as a shaking hand, will be removed alongside other small movements.

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2.2. Confidence Weighted Filtering

Confidence Weighted Filtering is another method that uses confidence values for smoothing. Data is given an assigned "confidence" value. The lower the confidence, the more heavily smoothed that data point would be [SSQ*16].

Confidence Weighted Temporal filtering works quite well with monocular motion capture because pose estimates contain a confidence value. However, during fast motion, smoothing may be less accurate than that of the One Euro Filter.

2.3. Our Approach (Adaptive Velocity Confidence Smoothing)

We have found that combining the One Euro Filter with Confidence Weighted Temporal Filtering together provides a more robust smoothing algorithm, one that we call "Adaptive Velocity Confidence Smoothing". The approach combines velocity-aware filtering, confidence-weighted modulation, and linear interpolation. It operates as a pre-processing stage before retargeting.

It begins by estimating the frame-to-frame change in joint position ($\mathbf{P}$). In the case of 3D pose data, we capture the velocity by measuring the change in position.

$$v_i = \|\mathbf{P}_n - \mathbf{P}_{n-1}\| = \sqrt{(x_n - x_{n-1})^2 + (y_n - y_{n-1})^2 + (z_n - z_{n-1})^2}$$

Instead of a threshold value to blend between α_{slow} and α_{fast}, a sigmoid function is used to calculate a resulting α_{vel}. Here, v_i is the joint velocity, v_0 is the transition midpoint, and k controls the steepness of the sigmoid.

$$\alpha_{\text{vel}}(v_i) = \alpha_{\min} + (\alpha_{\max} - \alpha_{\min}) \cdot \frac{1}{1 + \exp\Big(k(v_i - v_0)\Big)}$$

$$\alpha_{\text{conf}} = \text{clamp}(c, 0.2, 1.0)$$

α_{vel} is then combined with α_{conf}, the smoothing coefficient using the same theory as Confidence Weighted Temporal Filtering.

$$\alpha_{\text{final}} = \alpha_{\text{vel}} \cdot \alpha_{\text{conf}}$$

The confidence term and final alpha are clamped so that min-max smoothing settings can be applied for further control. The final step linearly interpolates the joint displacement according to the adaptive α_{final}, and the resulting positions are forwarded to the retargeting and locomotion modules to construct the final pose.

$$\mathbf{S}_n = \mathbf{S}_{n-1} + \alpha_{\text{final}} (\mathbf{P}_n - \mathbf{S}_{n-1})$$

3. Conclusion and Future Work

The smoothing filter suppresses high-frequency variations while preserving global structure as shown in Figure 2. The velocity standard deviation decreased by 0.4%, while the maximum absolute step change decreased by 46.3%. These metrics indicate effective attenuation of “jitter” with negligible impact on overall motion.

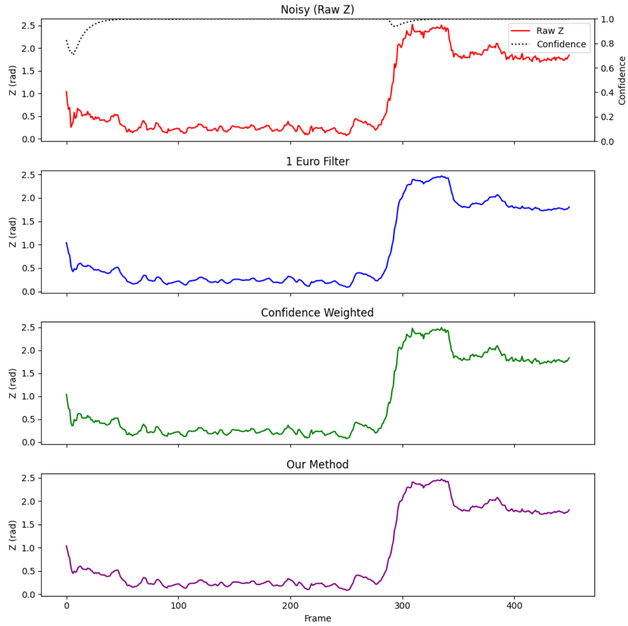

Figure 2: *Comparison between Adaptive Velocity-Confidence Smoothing, One Euro Filter and Confidence Weighted Filtering*

The algorithm was implemented in Deadshot, a web-based motion-capture application: `https://cjhosken.github.io/deadshot/`. The tool uses modern AI pose-estimation models and makes them accessible through the web. It can be used alongside digital content creation tools. The main limitation is the quality of the pose-estimation model and retargeting. Future work will focus on training a web-based pose-estimation model with accurate depth prediction.

References

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