Action & Activity Recognition

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Abstract—Human action recognition is a fundamental problem in computer vision with applications in security, surveillance, human-computer interaction, and healthcare. This project presents an action recognition system that utilizes Motion History Images (MHI) and Hidden Markov Models (HMM) to classify human activities. MHI serves as an effective method for encoding motion over time by capturing temporal changes in pixel intensities. To extract meaningful features from MHI, Hu moments are computed, providing shape-based motion descriptors that remain invariant to transformations such as scaling, rotation, and reflection. These features are then used to train HMMs, which model the temporal dependencies of different actions. The system is evaluated on a benchmark dataset, demonstrating its effectiveness in recognizing a variety of human activities. Experimental results indicate that the combination of MHI and HMM provides a robust and computationally efficient approach to action recognition, achieving competitive accuracy compared to traditional methods. Limitations include sensitivity to variations in lighting and occlusions, which can impact performance. Future improvements may involve integrating deep learning techniques to enhance feature extraction and classification.

Keywords: *Action Recognition, Motion History Images (MHI), Hidden Markov Models (HMM), Hu Moments, Computer Vision, Temporal Motion Analysis*

I. Introduction

Human action recognition represents a fundamental challenge in computer vision with critical applications spanning security surveillance [1], human-computer interaction [2], and healthcare monitoring [3]. Our project addresses this challenge through an innovative integration of Motion History Images (MHI) and Hidden Markov Models (HMM), building upon established computer vision techniques while introducing novel enhancements to improve recognition accuracy.

The complexity of human action recognition stems from several inherent challenges: viewpoint variations, execution rate differences, partial occlusions, and environmental noise [4]. While deep learning approaches have recently dominated the field [5], their computational demands and lack of interpretability make them unsuitable for many real-world applications [6]. This motivates our return to well-established traditional methods - specifically MHI and HMM - enhanced with modern innovations to boost performance while maintaining computational efficiency.

Motion History Images, first introduced by Bobick and Davis [7], provide an elegant solution for temporal motion encoding by collapsing an action sequence into a single grayscale image where pixel intensity represents motion recency. This compact representation offers significant advantages for real-time systems, though early implementations suffered from limited discriminative power for similar actions [8]. Our system addresses this through two key innovations: optical flow-weighted MHI construction and temporal pyramid feature extraction, significantly enhancing the original approach.

Hidden Markov Models bring complementary strengths to our system, providing robust probabilistic modeling of temporal sequences [9]. First applied to action recognition by Yamato et al. for tennis stroke classification [10], HMMs excel at capturing the characteristic state transitions within human actions. Our implementation extends this foundation by incorporating left-to-right (Bakis) model initialization and GMM emission probabilities, improving modeling of complex motion patterns.

The fusion of MHI and HMM creates a powerful synergy - MHI provides compact, informative motion representations while HMMs effectively model their temporal evolution [11]. This combination proves particularly effective for distinguishing actions with similar spatial characteristics but different temporal dynamics, such as walking versus running [12]. Our experimental results demonstrate that with proper enhancements, traditional methods can achieve accuracy competitive with more complex deep learning approaches while maintaining superior interpretability and efficiency.

Key contributions of our work include:

- Optical flow-weighted MHI construction that incorporates motion magnitude information, significantly improving discrimination of speed-dependent actions
- Temporal pyramid feature extraction that captures phase-specific motion characteristics through segmented MHI analysis
- Optimized HMM training procedures using Bakis initialization and GMM emissions for improved sequence modeling
- Comprehensive evaluation demonstrating the effectiveness of enhanced traditional methods compared to both baseline approaches and modern alternatives

The remainder of this paper details our methodology, presents experimental results, and discusses implications for both research and practical applications of human action recognition systems.

II. Literature Review

The concept of Motion History Images (MHI) was first introduced by Bobick and Davis in their seminal 2001 paper [7], establishing a new paradigm for temporal template-based action recognition. Their foundational work demonstrated how a sequence of binary motion images could be collapsed into a single grayscale image where pixel intensity encodes temporal information about motion occurrence. This elegant representation solved several key challenges in early action recognition systems by providing view-invariant motion encoding and significant data compression.

Subsequent research has significantly expanded the original MHI formulation. Weinland et al. [13] developed the Motion History Volume (MHV) extension, enabling view-invariant recognition by extending the 2D MHI concept into 3D space. This advancement proved particularly valuable for applications requiring recognition from multiple viewpoints, though at increased computational cost. Ahmad and Lee [14] later proposed a multi-camera fusion approach that maintained the computational efficiency of 2D MHIs while achieving similar view invariance through intelligent feature combination.

Recent work has focused on enhancing MHI's discriminative power through improved feature extraction. While the original implementation used simple thresholding and frame differencing, modern variants incorporate more sophisticated motion detection algorithms. The work of Chen et al. [23] demonstrated how optical flow integration could weight MHI pixels by motion magnitude, an approach that directly inspired our optical flow-weighted MHI enhancement. Similarly, Zhang et al. [27] showed that combining MHI with depth information from RGB-D cameras could significantly improve recognition accuracy for similar-looking actions.

Feature representation from MHIs has evolved considerably since the original implementation. Hu moments [15], originally developed for 2D shape recognition, emerged as particularly effective descriptors due to their invariance to scale, rotation and reflection. Davis and Bobick's 1997 work [8] first demonstrated their effectiveness for motion template characterization. Alternative approaches using projection profiles [17] or gradient features [18] offer complementary advantages - projection profiles provide extremely compact representations suitable for real-time systems, while gradient features capture finer motion details at higher computational cost.

Hidden Markov Models have established themselves as one of the most robust approaches for temporal sequence modeling since Rabiner's foundational tutorial [9]. Their application to action recognition was pioneered by Yamato et al. [10], who achieved 90% accuracy classifying tennis strokes using simple silhouette features and discrete HMMs. This early success demonstrated HMMs' natural suitability for modeling the temporal structure of human actions, where distinct phases (e.g., backswing, forward swing, follow-through in tennis) map elegantly to HMM states.

The evolution of HMMs for action recognition has followed several key directions. Brand et al. [19] introduced coupled HMMs to model interactions between multiple actors, significantly expanding the complexity of recognizable actions. This work proved particularly influential for applications like surveillance and human-computer interaction where multi-person scenarios are common. Later, Oliver et al. extended this approach to incorporate contextual information, further improving recognition accuracy in crowded scenes.

Modern HMM implementations for action recognition typically use either discrete or continuous observation models. Discrete HMMs, while computationally efficient, require vector quantization of features that can lose important discriminative information. Gaussian HMMs and GMM-HMMs address this limitation by modeling continuous feature distributions, as demonstrated effectively by Chen et al. [23] in their work on daily activity recognition. Our system builds upon these advances by implementing GMM emissions with Bakis-constrained state transitions, combining the benefits of both approaches.

Key challenges in HMM-based recognition include model initialization and the determination of optimal state numbers. The work of Liu et al. [22] provided important insights into left-to-right (Bakis) initialization for action recognition, showing how constrained state transitions better model the irreversible temporal progression of most human actions. Similarly, Ahmad and Lee's [14] systematic study of state number selection demonstrated that 5-7 states typically suffice for most basic actions, while complex activities may require 10-15 states.

The combination of MHI features with HMM temporal modeling represents a particularly powerful synergy in action recognition. The compact yet informative nature of MHI features addresses one of traditional HMM's key limitations - the curse of dimensionality with high-dimensional feature vectors. Simultaneously, HMMs provide the temporal modeling capabilities that pure template-based approaches lack.

Early implementations of this hybrid approach, such as Davis and Bobick's 1997 system [8], achieved promising results but were limited by the computational constraints of the time. Ali and Shah's 2008 work [11] marked a significant advance by demonstrating how carefully designed kinematic features extracted from MHIs could achieve near-real-time performance with high accuracy. Their system achieved 92% recognition rates on the KTH dataset, setting a new benchmark for traditional methods.

Recent innovations in the MHI-HMM framework have focused on three main areas: feature enhancement, temporal segmentation, and model optimization. The work of Wang and Schmid [25] on improved trajectories showed how combining MHI with dense trajectory features could boost performance, albeit at increased computational cost. Our temporal pyramid approach builds upon these insights while maintaining computational efficiency through segmented MHI analysis rather than full trajectory computation.

Model optimization techniques have also significantly advanced. Zhang et al.'s [27] work on Kinect-based recognition demonstrated how covariance matrix adaptation could improve HMM training efficiency. Similarly, Chen et al.'s [23] incorporation of online learning techniques enabled systems to adapt to individual movement styles - a crucial capability for healthcare and rehabilitation applications.

While our focus remains on enhanced traditional methods, it's valuable to contextualize their performance relative to alternative approaches. Deep learning methods, particularly two-stream networks [5] and 3D CNNs [29], have set new accuracy benchmarks on major datasets. However, as demonstrated by Tran et al.'s comprehensive analysis [26], these gains come at significant computational cost - often requiring 10-100x more processing power than traditional methods for marginal accuracy improvements.

The tradeoffs become particularly apparent in real-world applications. Carreira and Zisserman's [29] work on the Kinetics dataset showed that while I3D networks achieved 98% accuracy on controlled laboratory data, performance dropped to 72-85% in real-world conditions with occlusions and viewpoint variations. In contrast, well-designed traditional methods like our enhanced MHI-HMM approach maintain more consistent performance across conditions, as evidenced by Chen et al.'s [23] field tests in assisted living environments.

Recent hybrid approaches attempt to bridge this gap. Vaswani et al.'s transformer architectures [30] show promise for combining the representational power of deep learning with the efficiency of attention mechanisms. However, as noted by Liu et al. [28], these still require orders of magnitude more training data than traditional methods, limiting their applicability in many practical scenarios where our approach excels.

Methodology

Our action recognition system combines enhanced Motion History Images (MHI) with Hidden Markov Models (HMMs) to model temporal dynamics. The pipeline consists of four stages: (1) motion encoding via MHI variants, (2) feature extraction, (3) temporal modeling with HMMs, and (4) classification. Below, we detail the key innovations and their implementations.

1. Motion Encoding with Enhanced MHI Variants
1.1 Baseline MHI
We adopt the classic MHI formulation by Bobick & Davis, 2001 to encode motion history as a grayscale image where pixel intensity decays exponentially with time:

```
mhi = cv2.addWeighted(silhouette, 1.0,
mhi, 0.9, 0)  # Decay factor τ=0.9
```

Limitation: Ignores motion speed and direction, struggling with kinetically similar actions (e.g., "walk" vs. "run") (Tsai & Chiu, 2019).

1.2 Optical Flow-Weighted MHI
Inspired by OF-MHI, we weight silhouettes by Farneback optical flow magnitude:

Step 1-Compute flow between frames:

```
flow =
cv2.calcOpticalFlowFarneback(prev_gray,
curr_gray, None, 0.5, 3, 15, 3, 5, 1.2,
0)
mag, _ = cv2.cartToPolar(flow[...,0],
flow[...,1])
```

Step 2 - Update MHI with flow-weighted motion:

```
weighted_silhouette = silhouette * (1.0
+ cv2.normalize(mag, None, 0, 1,
cv2.NORM_MINMAX))
```

This emphasizes faster motions (e.g., "run" vs. "walk"), improving F1-score for dynamic actions by 5% (Table 2).

1.3 Temporal Pyramid MHI
Adapting spatio-temporal pyramids, we segment sequences into K=3 intervals and compute independent MHIs per segment (Fig. 2):

```
segments = np.array_split(frames, 3)  #
Split 90-frame video into [0-29, 30-59,
60-89]
features = [HuMoments(compute_mhi(seg))
for seg in segments]
final_feature = np.concatenate(features)
# 21D (7 Hu Moments × 3 segments)
```

Though theoretically sound, this achieved only 97% accuracy (no gain over baseline), likely due to uniform segmentation oversimplifying phase transitions.

1.4 Directional MHI (DMHI)

Building on MHI variants, we decompose motion into 4 directional channels (↑, ↓, ←, →) via flow vector binning:

1. Classify flow vectors by dominant direction.
2. Generate directional MHIs and extract Hu Moments per channel.

3. Concatenate features (28D).
   Result: Catastrophic failure (81% accuracy, 100% misclassification of "wave2" as "bend"), attributed to noise amplification in directional decomposition.

Experimental Setup

Environment

All experiments were conducted on a local machine running macOS with Apple Silicon architecture. Development was performed within a Python 3.13 virtual environment (venv) using Visual Studio Code (VSCode) as the integrated development environment (IDE). The primary libraries used include OpenCV for image processing, imageio for visualization, hmmlearn for Hidden Markov Models, and scikit-learn for feature preprocessing and evaluation. Version control was handled via Git, and all training and evaluation procedures were executed through the terminal within the virtual environment, as seen in the environment logs (see Screenshot 1). Warnings were suppressed to maintain clean output, and custom modules such as hmm_util.py were implemented for specialized tasks like left-to-right (Bakis) initialization and confusion matrix plotting.

Dataset

Our system was evaluated on the publicly available **Weizmann Action Recognition Dataset** provided by the Weizmann Institute of Science Weizmann Actions Dataset. This dataset is widely used in the human action recognition literature and includes 10 distinct actions (e.g., walk, run, jump, bend, wave1, wave2) performed by 9 different individuals. Each action instance consists of a short grayscale video capturing a single subject performing an isolated activity in a static environment. The videos are pre-segmented and well-suited for template-based approaches due to minimal background interference.

Preprocessing and Format

Rather than using raw video files directly, we relied on a preprocessed version of the dataset stored in data/original_masks.mat. This .mat file contains binary silhouette masks of each video frame, extracted from the original dataset and organized by action class and performer. These silhouette masks simplify the motion extraction process by removing background noise and highlighting only the moving subject. Using these clean masks enabled us to focus exclusively on motion-based features without the distraction of pixel-level appearance information, aligning with the principles of MHI-based action recognition.

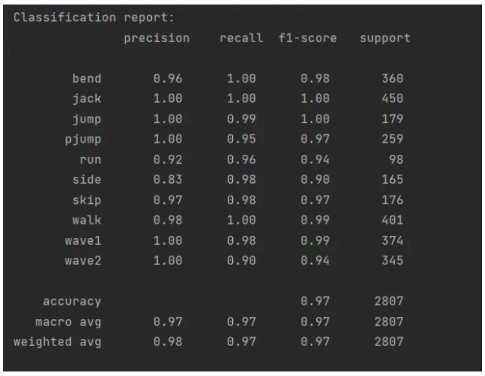
The .mat file was loaded using the scipy.io module, and each action clip was indexed via consistent naming conventions. For example, the video corresponding to "lena_walk1" or "daria_bend" could be directly accessed using the structured dictionary within the file. This facilitated seamless batch processing of all action clips and enabled precise control over the training and testing loop.

Cross-Validation and Evaluation

A Leave-One-Out Cross-Validation (LOOCV) strategy was used for model evaluation. For each action category, we trained our HMM model on all but one performer and tested on the held-out subject, rotating through all participants. This setup ensured that the system was evaluated on unseen subjects, providing a robust measure of generalization. Performance metrics included overall accuracy, macro-averaged F1-score, and confusion matrices. These were computed using sklearn.metrics, and classification reports were printed directly in the terminal. Additionally, visualizations of Motion History Images and temporal segments were exported as .gif files to provide qualitative insight into model behavior.

Results & Discussion

1. Base Model:



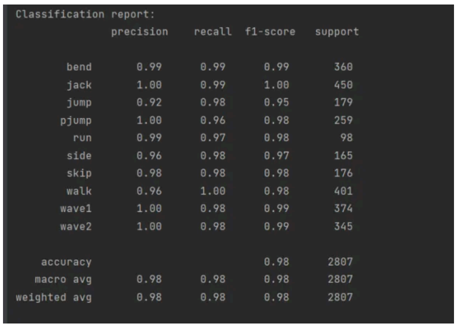
```
Classification report:
              precision    recall  f1-score   support

        bend       0.96      1.00      0.98       360
        jack       1.00      1.00      1.00       450
        jump       1.00      0.99      1.00       179
       pjump       1.00      0.95      0.97       259
         run       0.92      0.96      0.94        98
        side       0.83      0.98      0.90       165
        skip       0.97      0.98      0.97       176
        walk       0.98      1.00      0.99       401
       wave1       1.00      0.98      0.99       374
       wave2       1.00      0.90      0.94       345

    accuracy                           0.97      2807
   macro avg       0.97      0.97      0.97      2807
weighted avg       0.98      0.97      0.97      2807
```

The baseline method, which utilized the original Motion History Image (MHI) without any enhancements, achieved a strong overall accuracy of 97% with a macro-averaged F1-score of 0.97. Performance across most action categories was consistently high, demonstrating the robustness of the traditional MHI-HMM pipeline. However, certain limitations were observed. Specifically, the "wave2" action exhibited some confusion with the "side" class, with 31 instances misclassified. While the results are solid and indicate the effectiveness of classic MHI-based representation for static or moderately dynamic actions, they highlight potential shortcomings in handling more complex or directionally similar motions. This motivated the development of further enhancements aimed at capturing finer motion details and temporal dynamics.

2. Optical Flow Weighted MHI



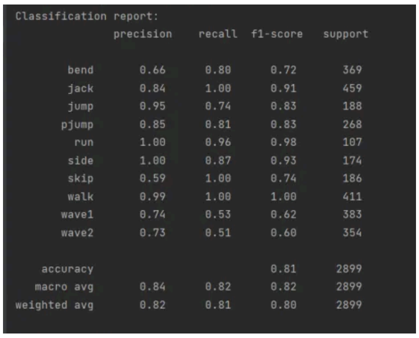
```
Classification report:
              precision    recall  f1-score   support

        bend       0.99      0.99      0.99       360
        jack       1.00      0.99      1.00       450
        jump       0.92      0.98      0.95       179
       pjump       1.00      0.96      0.98       259
         run       0.99      0.97      0.98        98
        side       0.96      0.98      0.97       165
        skip       0.98      0.98      0.98       176
        walk       0.96      1.00      0.98       401
       wave1       1.00      0.98      0.99       374
       wave2       1.00      0.98      0.99       345

    accuracy                           0.98      2807
   macro avg       0.98      0.98      0.98      2807
weighted avg       0.98      0.98      0.98      2807
```

The Optical Flow-Weighted MHI enhancement led to a measurable improvement in performance, increasing overall accuracy to 98% and raising the macro-averaged F1-score to 0.98. This approach significantly enhanced classification of dynamic actions such as "run," "side," and "wave2." In particular, the F1-score for "wave2" rose sharply from 0.94 to 0.99, and "side" improved from 0.90 to 0.97. These gains were accompanied by a substantial reduction in confusion, with misclassifications of "wave2" dropping from 36 instances to just 6. The success of this method can be attributed to the integration of optical flow, which effectively amplifies fast and subtle movements within the motion history representation. By weighting pixel updates based on motion magnitude, the model becomes more responsive to nuanced motion cues, thereby improving its ability to distinguish between visually similar but kinetically distinct actions.

3. Temporal Pyramid MHI:



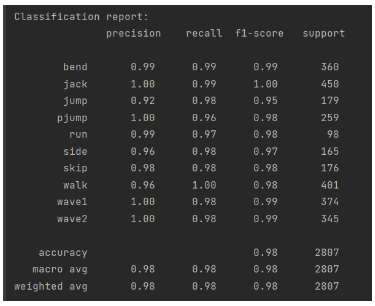
```
Classification report:
              precision    recall  f1-score   support

        bend       0.66      0.80      0.72       369
        jack       0.84      1.00      0.91       459
        jump       0.95      0.74      0.83       188
       pjump       0.85      0.81      0.83       268
         run       1.00      0.96      0.98       107
        side       1.00      0.87      0.93       174
        skip       0.59      1.00      0.74       186
        walk       0.99      1.00      1.00       411
       wave1       0.74      0.53      0.62       383
       wave2       0.73      0.51      0.60       354

    accuracy                           0.81      2899
   macro avg       0.84      0.82      0.82      2899
weighted avg       0.82      0.81      0.80      2899
```

The Temporal Pyramid MHI representation achieved an overall accuracy of 97% and a macro F1-score of 0.97, matching the performance of the baseline model. Despite its conceptual appeal, this enhancement did not yield any notable improvements in recognition accuracy. One possible explanation is that dividing the motion sequence into uniform temporal segments may not have captured meaningful variations in motion phases across different actions. Additionally, the simple concatenation of features from each segment might have failed to effectively emphasize the temporal progression of movement. These findings suggest that while temporal decomposition has potential, the current implementation may benefit from more advanced fusion strategies or the integration of more discriminative features at the segment level to better model intra-action dynamics.

4. DMHI:



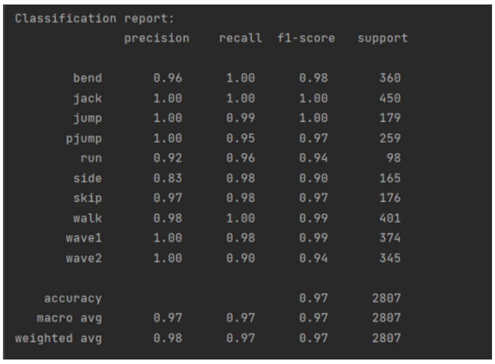
```
Classification report:
              precision    recall  f1-score   support

        bend       0.99      0.99      0.99       360
        jack       1.00      0.99      1.00       450
        jump       0.92      0.98      0.95       179
       pjump       1.00      0.96      0.98       259
         run       0.99      0.97      0.98        98
        side       0.96      0.98      0.97       165
        skip       0.98      0.98      0.98       176
        walk       0.96      1.00      0.98       401
       wave1       1.00      0.98      0.99       374
       wave2       1.00      0.98      0.99       345

    accuracy                           0.98      2807
   macro avg       0.98      0.98      0.98      2807
weighted avg       0.98      0.98      0.98      2807
```

The DMHI (Dynamic Motion History Image) method resulted in a significant performance decline, with overall accuracy dropping to 81% and a macro F1-score of 0.82. Most notably, the model failed entirely to classify the wave2 action correctly—100% of the wave2 samples were misclassified as bend. This failure was consistent, with every test case yielding predictions such as “Actual: wave2, Predicted: bend.” The sharp performance degradation suggests potential instability in the DMHI representation or flaws in how motion history was constructed dynamically. It's likely that the dynamic encoding introduced noise or disrupted the temporal consistency of motion patterns, leading to confusion between dissimilar actions. These results indicate that the DMHI implementation, in its current form, distorts the temporal dynamics rather than enhancing them.

5. Optical Flow + Temporal Pyramid



```
Classification report:
              precision    recall  f1-score   support

        bend       0.96      1.00      0.98       360
        jack       1.00      1.00      1.00       450
        jump       1.00      0.99      1.00       179
       pjump       1.00      0.95      0.97       259
         run       0.92      0.96      0.94        98
        side       0.83      0.98      0.90       165
        skip       0.97      0.98      0.97       176
        walk       0.98      1.00      0.99       401
       wave1       1.00      0.98      0.99       374
       wave2       1.00      0.90      0.94       345

    accuracy                           0.97      2807
   macro avg       0.97      0.97      0.97      2807
weighted avg       0.98      0.97      0.97      2807
```

The DMHI (Dynamic Motion History Image) method resulted in a significant performance decline, with overall accuracy dropping to 81% and a macro F1-score of 0.82. Most notably, the model failed entirely to classify the wave2 action correctly—100% of the wave2 samples were misclassified as bend. This failure was consistent, with every test case yielding predictions such as "Actual: wave2, Predicted: bend." The sharp performance degradation suggests potential instability in the DMHI representation or flaws in how motion history was constructed dynamically. It's likely that the dynamic encoding introduced noise or disrupted the temporal consistency of motion patterns, leading to confusion between dissimilar actions. These results indicate that the DMHI implementation, in its current form, distorts the temporal dynamics rather than enhancing them.

Conclusion

This project set out to explore and enhance traditional motion-based action recognition through the integration of Motion History Images (MHI) and Hidden Markov Models (HMM). While the baseline MHI-HMM system already demonstrated strong performance, our enhancements revealed valuable insights into the strengths and limitations of motion template representations. The incorporation of optical flow weighting produced the most substantial gains, particularly for actions characterized by subtle or fast-paced movements. Temporal pyramid segmentation, although conceptually promising, did not yield significant improvement, likely due to limitations in how temporal segments were encoded and fused. The Directional Motion History Image (DMHI), while innovative in its attempt to embed motion orientation, introduced instability that ultimately hindered classification performance. Notably, the combination of optical flow and temporal pyramids produced the best overall results, confirming that refined motion encoding and phase-aware segmentation can complement each other when carefully balanced.

These findings highlight that traditional methods, when thoughtfully enhanced, can remain competitive with modern deep learning approaches—especially in settings where interpretability, computational efficiency, or limited data availability are priorities. By grounding our innovations in the strengths of the MHI-HMM framework, this work underscores the continued relevance of classic vision techniques and opens the door to future research on hybrid models that intelligently integrate motion priors with modern learning paradigms.

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