

Literature Survey on Skeleton Tracking and Identity Association

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1 Introduction

Human skeleton tracking has gained popularity in applications like surveillance, motion analysis, and human-computer interaction. This survey reviews key models, their performance, and methods to assign identities to tracked skeletons.

2 Skeleton Tracking Models

Several deep learning models enable human pose estimation:

- **OpenPose** – Multi-person pose estimation framework with high accuracy [1].
- **MediaPipe** – Lightweight and real-time tracking from Google [2].
- **HRNet** – High-resolution deep network for detailed pose estimation [3].
- **PoseNet** – Mobile-friendly pose estimation framework [4].

3 Performance Comparisons

Table 1 shows a comparison of models based on frames per second (FPS) and mean average precision (mAP).

Model	FPS	mAP
OpenPose	8	61.8
MediaPipe	30	55.1
HRNet	12	70.0
PoseNet	22	45.6

Table 1: Performance of Skeleton Tracking Models

4 Identity Assignment to Tracked Skeletons

Assigning an identity to a detected and tracked skeleton is a crucial step in ensuring continuity in multi-person tracking, particularly when a person’s face is not always visible. This process involves a combination of **face recognition**, **re-identification (ReID) models**, and **temporal tracking methods**.

4.1 Face Recognition for Initial Identification

When a person first appears in the scene with their face visible, face recognition algorithms are used to associate the detected skeleton with a specific identity. State-of-the-art deep learning-based face recognition models, such as *FaceNet* [5] and *ArcFace* [6], extract facial embeddings that uniquely represent an individual. The process follows these steps:

- Detect the face using a face detection model (e.g., *MTCNN* [7], *RetinaFace* [8]).

- Extract facial embeddings using a pre-trained deep learning model.
- Compare the embeddings with a database of known individuals using a similarity metric (e.g., cosine similarity).
- If the face matches an existing identity, assign that ID to the detected skeleton; otherwise, register the person as a new identity.

4.2 Tracking Skeletons Across Frames

Once an identity is assigned to a skeleton, tracking models ensure that the same identity is preserved across consecutive frames. This is achieved using:

- **Kalman Filters:** A probabilistic model that predicts the next position of the skeleton based on its previous states.
- **SORT (Simple Online and Realtime Tracker)** [9]: A lightweight tracking algorithm that combines detection with Kalman filters and Hungarian matching.
- **DeepSORT** [10]: An improved version of SORT that integrates deep learning-based feature embeddings for robust tracking.

These tracking models help maintain the identity of individuals even when faces are not visible by relying on **pose consistency** and **motion continuity**.

4.3 Re-Identification (ReID) When Face Becomes Occluded

If a person’s face is no longer visible, the system must track and recognize them using alternative methods. This is where **person re-identification (ReID)** models become essential. ReID models extract deep feature embeddings from the skeleton and body shape, allowing the system to match the skeleton to a previously identified individual. Approaches include:

- **Pose-Guided ReID** [11]: Uses body keypoints to extract discriminative features for identity matching.
- **Appearance-Based ReID** [12]: Uses clothing color and texture features to recognize individuals.
- **Gait-Based Recognition** [13]: Tracks unique movement patterns to distinguish individuals, even when facial features are not available.

By combining these methods, a robust skeleton tracking system can continuously track individuals across a scene, preserving identity even in cases of temporary occlusion.

5 Conclusion

Real-time skeleton tracking is feasible with existing models, and identity assignment can be improved with face recognition or re-identification networks. Future work should focus on combining multimodal identity cues.

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