A Survey on 3D Egocentric Human Pose Estimation

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Abstract

Egocentric human pose estimation aims to estimate human body poses and develop body representations from a firstperson camera perspective. It has gained vast popularity in recent years because of its wide range of applications in sectors like XR-technologies, human-computer interaction, and fitness tracking. However, to the best of our knowledge, there is no systematic literature review based on the proposed solutions regarding egocentric 3D human pose estimation. To that end, the aim of this survey paper is to provide an extensive overview of the current state of egocentric pose estimation research. In this paper, we categorize and discuss the popular datasets and the different pose estimation models, highlighting the strengths and weaknesses of different methods by comparative analysis. This survey can be a valuable resource for both researchers and practitioners in the field, offering insights into key concepts and cutting-edge solutions in egocentric pose estimation, its wideranging applications, as well as the open problems with future scope.

Index Terms- 3D egocentric human pose estimation, deep learning models, datasets, evaluation metrics.

1 Introduction

Human pose estimation has been a longstanding challenge in computer vision with the goal of accurately determining a person's body pose [1, 2, 3, 4]. It has gained prominence due to its relevance in numerous applications, ranging from animation and gaming to surveillance, healthcare, and human-computer interaction. In the current era dominated by XR-technology and the evolution of human-computer interaction, there exists an increasing demand for precise methodologies to track and comprehend human movements. This need is particularly enhanced when considering the perspective of camera wearers, whose viewpoints offer unique insights into the dynamics of human motion.

Egocentric pose estimation is a specialized subset of 3D human pose estimation that focuses on estimating the pose of the person from the point of view of a wearable camera or device worn by the person (first person perspective). Unlike traditional pose estimation, which relies on external cameras or sensors, egocentric pose estimation offers a unique and immersive perspective on human body representation. Real-time processing, adaptability to different environments, user interaction mechanisms, including gestures, and semantic scene understanding

contribute to the effectiveness of egocentric pose estimation systems. Figure 1 shows a visual demonstration of the difference between traditional 3D pose estimation and egocentric 3D pose estimation.

The rise of wearable technology, including smart glasses, body-mounted cameras, and head-mounted displays has significantly fueled interest in egocentric pose estimation. These devices have given researchers and developers unprecedented access to the wearer's field of view. Through this technology, users can interact with their digital environment in a natural and intuitive manner, enhancing the overall user experience. Egocentric pose estimation plays a crucial role across various domains, facilitating intuitive interactions and insights. Its applications encompass Human-Computer Interaction (HCI) for gesture recognition, enhancing augmented and virtual reality experiences by tracking body movements, healthcare for precise therapy monitoring, biomechanical analysis in sports training, and enhancing realism in professional simulations through accurate movement replication.

This survey aims to explore the multifaceted aspects of egocentric human pose estimation. We delve into the fundamental principles, state-of-the-art methodologies, and the latest advancements in this emerging field. By doing so, we seek to provide a comprehensive overview for researchers and practitioners, offering valuable insights into the opportunities and challenges presented by egocentric pose estimation.

1.1 Challenges

Egocentric pose estimation comes with several challenges, stemming from the complexity of accurately capturing and interpreting human movements from the first-person perspective. Some of the key challenges include:

- Viewpoint Variations: The use of egocentric cameras, attached to the body, introduces challenges in pose estimation as body parts may be occluded, particularly when hidden from view. The wide range of possible viewpoints in egocentric settings, involving varying camera angles, heights, and orientations, demands robust models to ensure accurate pose estimation across diverse scenarios.
- Limited Depth Information: Egocentric cameras, commonly mounted on wearable devices, capture scenes in 2D, lacking explicit depth details. This absence complicates the accurate determination of the distance of body



Figure 1. Difference between (a) traditional human pose estimation [5] and (b) egocentric human pose estimation [6]

parts from the camera, as 2D images may project objects at different distances onto the same plane.

 Dataset Constraints: In-the-wild datasets are crucial for capturing real-world complexity, encompassing variations in lighting, backgrounds, activities, and environments. However, the scarcity of such datasets hinders model generalization, particularly in dynamic environments where users engage in various activities and encounter unpredictable situations. The limited availability of diverse samples in training datasets, often developed on motion capture systems, poses challenges for models aiming to handle real-world complexities in outdoor applications.

1.2 Scope of the Survey

Currently, there are numerous systematic surveys related to 2D and 3D human pose estimation on traditional and deep learning based approaches [7, 8, 9, 10] as well shape recovery based approaches [11, 12]. While comprehensive reviews on hand pose [13] and action recognition [14] from egocentric vision are present, it is noteworthy that, to the best of our knowledge, no comprehensive survey on full body egocentric 3D pose estimation methods has been published to date. This absence underscores a notable gap in existing research, despite the increasing interest and advancements in this domain. Hence, there is a pressing need for a comprehensive survey to offer a consolidated overview of state-of-the-art methodologies, challenges, and future directions in egocentric pose estimation.

In this paper, we first discuss different scopes and challenges of egocentric 3D human pose estimation. In section 2, different widely used datasets in pose estimation from egocentric visions have been illustrated. As discussed in section 3, egocentric pose estimation is divided into 2 main categories on the basis of output generation: skeletal based methods and human model based methods. Skeletal methods explore different egocentric models which are mostly regression based (estimation of 3D joint co-ordinates) and heatmap based (estimation of 2D heatmaps). On the other hand, Model based methods mainly generate human models using different shape recovery methods. Additionally, we present a comprehensive evaluation

of egocentric pose estimation models, showcasing various evaluation metrics in Section 4, a detailed performance analysis of state-of-the-art approaches on prominent datasets in Section 5. Lastly, we discuss the limitations and future research scopes for egocentric 3D pose estimation in Section 6.

2 Datasets

Large scale dataset is one of the key factors in visualizing and analysing a computer vision problem. Though there are many benchmark suite datasets like MPII Human Pose [15] and Human 3.6M [16] for traditional pose estimation, a notable gap exists in the availability of widely applicable benchmark dataset for egocentric pose estimation. Different proposed egocentric pose estimation methods have come up with their own datasets, most of which are constrained to motion capture systems in lab environments. In this section, we cover some popular datasets for 3D pose estimation in egocentric setup. Figure 2 showcases sample images from four different datasets. Table 1 lists the most popular datasets we found for egocentric pose estimation and also provides a concise overview of key features in each of them. Details for each dataset are provided in the text below.

EgoCap [21] proposed a method for creating large training datasets for body-part detection using a marker-less motion capture system. They leveraged eight fixed cameras to estimate 3D skeleton motion. They projected it onto fisheye images from a head-mounted camera setup, enhancing the dataset with background replacement, clothing color variations, and simulated lighting changes. The dataset is augmented using intrinsic recoloring and symmetry, doubling its size. The training set includes around 75,000 annotated fisheye images from six subjects, with two additional subjects for validation. This innovative approach minimizes manual annotation and improves model generalization.

Mo²Cap² [22] dataset addressed the challenge of acquiring annotated 3D pose data for training deep neural networks, specifically tailored to an egocentric fisheye camera setup. Manual labeling in 3D space is impractical, so marker-less multi-view motion capture is proposed for obtaining 3D annotations. However, obtaining a large, diverse set of annotated egocentric training examples using professional motion cap-









(a) Dataset setup for UnrealEgo [17]: Left image shows a glass equipped with two fisheye cameras. The middle image provides a third-person perspective of the person, offering context to the scene. The right image depicts the egocentric view of the person.









(b) Sample image from EgoPW [18] dataset visualizing egocentric view on the left image and exocentric view on the right image.

(c) Sample image from EgoGTA [19] dataset.

(d) Sample image from Wang et al.'s [20] dataset.

Figure 2. Sample images from different datasets used for egocentric human pose estimation.

ture systems is time-consuming. To overcome this, the authors introduced a synthetic training corpus by rendering a human body model from an egocentric fisheye view. The dataset is built upon the SURREAL [23] dataset, incorporating a variety of motions and body textures. Realistic training images are generated by mimicking real-world camera, lighting, and background scenarios. The synthetic dataset is comprised of 530,000 images with ground truth annotations of 2D and 3D joint positions, providing a diverse and extensive resource for training deep neural networks in egocentric pose estimation.

xr-EgoPose [24] provides an extensive collection of 383,000 frames featuring individuals showcasing a rich diversity of skin tones, body shapes, clothing styles, set with various backgrounds and lighting scenarios. Scenes are randomly generated from mocap data, featuring realistic body types like skinny short to full tall versions and skin tones from white to black. The dataset offers high resolution 8-bit images at 30 fps, accompanied by metadata on 3D joint positions, character height, and more. Prioritizing photorealism, the synthetic dataset is created through Maya animation with mocap data and V-Ray's physically based rendering setup.

In *EgoGlass* [25], the authors introduced a new dataset for egocentric human pose estimation captured using their *EgoGlass*, a wearable device resembling eyeglasses. The dataset

is obtained through a capture system comprising the Ego-Glass helmet for egocentric views and six external cameras for outside-in motion capture. The EgoGlass frame incorporates lightweight Raspberry Pi spy cameras to address visibility limitations posed by the user's nose or cheek. The authors used an outside-in motion capture setup with six cameras and employ the OpenPose [2] method for third-person view human pose estimation. The ground truth 3D pose is then projected onto the coordinate system of each body cam mounted on the eyeglass frame.

EgoBody [26] presents an unique large-scale egocentric dataset capturing 2-person interactions using a Microsoft HoloLens2 headset. Unlike previous datasets, it provided synchronized multi-modal data, including RGB, depth, head, hand, and eye gaze tracking. With 125 sequences from 36 subjects in 15 scenes, it offered accurate 3D human shape, pose, and motion ground-truth. The dataset aims to explore the relationships between human attention, interactions, and motions, overcoming limitations of prior datasets and advancing sociological and human-computer interaction research.

The *EgoPW* [18] dataset, a groundbreaking contribution, is the first in-the-wild human performance dataset captured by synchronized egocentric and external cameras. It features 10 actors, 20 clothing styles, and 20 actions from 318,000 frames

Dataset	Year	No. of Images	No. of Subjects / Ac-	Characteristics		
			tions			
EgoCap [21]	2016	100000	8 subjects	outside-in; marker-less motion capture system; an-		
				notated.		
$Mo^2Cap^2[22]$	2019	53000 images	3000 actions	annotated; 700 different body textures.		
xr-EgoPose	2019	383k frames	23 male and 23 female	synthetic; scene is generated from randomized char-		
[24]			subjects; 9 actions	acters, environments, lighting rigs and animation.		
EgoGlass	2021	173577 frames	10 subjects; 6 actions	outside-in capture; every frame contains two views,		
[25]				each captured by a body cam attached to the eyeglass		
				frame.		
EgoBody	2022	219,731 frames	15 indoor scenes; 36	two subjects (camera wearer and interactee) in-		
[26]			subjects	volved in different interaction scenarios.		
EgoPW [18]	2022	318k frames	10 subjects; 20 actions	in-the-wild real data; 20 different clothing styles.		
UnrealEgo	2022	900000 images	17 subjects; 30 actions	450k in-the-wild stereo views; Motions, 3D environ-		
[17]				ments, spawning human characters.		
EgoGTA	2023	320k frames	101 different actions	synthetic; based on GTA-IM containing different		
[19]				daily motions and scene geometry.		
ECHP [27]	2023	30 video sequences;	9 subjects; 10 daily ac-	indoor and outdoor; real-world data.		
		75000 frames	tions			
First2Third-	2023	1950 video se-	14 subjects; 40 actions	indoors and outdoors environments, activities in-		
Pose[28]		quences for 2.5		clude sports actions and daily tasks.		
		hours at 25 fps.				
Ego-Exo4D	2023	5625 video se-	839 subjects; 43 ac-	131 different scenes in 13 different cities; comprises		
[29]		quences for 1422	tions	skilled human activities (e.g., sports, music, dance,		
		hours.		bike repair).		

Table 1. Popular datasets for egocentric 3D pose estimation.

organized into 97 sequences. The dataset introduced 3D poses as pseudo labels, enhancing its significance for in-the-wild 3D pose estimation research.

The *UnrealEgo* [17] dataset is introduced for robust egocentric 3D human motion capture (MoCap). The dataset includes 17 diverse 3D human models exhibiting various motions in 14 realistic environments. With more than 45,000 motions, UnrealEgo outperformed existing mocap datasets. Stereo fisheye images and depth maps are rendered with high motion variety, capturing complex activities like breakdance and backflips. The dataset provides metadata, including 3D joint positions and camera information, and comprises 450,000 inthe-wild stereo views. UnrealEgo showcases motion diversity through wider joint position distributions compared to xR-EgoPose [24], making it a valuable resource for comprehensive egocentric 3D human motion research. Furthermore, the authors introduced two more benchmark dataset UnrealEgo2 and UnrealEgo-RW (RealWorld) [30] datasets which offer a much larger number of egocentric stereo views with a wider variety of human motions than the existing datasets.

The *EgoGTA* [19] dataset is introduced for accurate human pose and scene geometry ground truth in training, leveraging the diverse daily motions and ground truth scene geometry of GTA-IM. The methodology involves fitting the SMPL-X [31] model to 3D joint trajectories from GTA-IM, followed by attaching a virtual fisheye camera to the forehead of the SMPL-X [31] model for generating synthetic images, semantic labels, and depth maps with and without the human body. The dataset

comprises 320,000 frames across 101 sequences with distinct human body textures.

ECHP [27] dataset addresses 3D human motion estimation from egocentric videos. The dataset includes 65000 training images with third-person and egocentric views, 10k validation images, and a test set with egocentric images and 3D ground truth from VICON Mocap. Egocentric poses are the primary focus. OpenPose [2] extracts 2D joints, and a pretrained model handles human segmentation. Cameras are well-calibrated and Aruco marker [32] aided in obtaining egocentric camera pose. The dataset comprises 30 sequences with 9 subjects and 20 textures performing 10 actions in diverse indoor/outdoor scenes. The test set features 4 unseen subjects, emphasizing generalization. The VICON system captured 17k frames with 3D ground truth in the same indoor setting.

The *First2Third-Pose* [28] dataset presents a diverse collection of short videos capturing 14 individuals engaged in 40 activities. Utilizing head-mounted cameras for egocentric views and static cameras for side and front perspectives, the dataset ensures a comprehensive exploration of human poses in indoor and outdoor settings. Synchronization is achieved through participants clapping before each activity, offering aligned views for enhanced analysis. With 1950 activity sequences lasting 8 to 25 seconds, this dataset addresses the need for synchronized views and facilitating a deeper understanding of actions in both first and third-person perspectives.

Ego-Exo4D [29] is a groundbreaking multimodal dataset and benchmark suite, offering the largest public collection of

time-synchronized first and third-person videos captured by 839 individuals across 131 scenes in 13 cities. This unique dataset is comprised of 1,422 hours of video, featuring both egocentric and multiple synchronized exocentric views. Notably, it introduces the "EgoPose" benchmark, focusing on recovering 3D body and hand movements from egocentric videos. The task involves estimating 17 3D body joint positions and 21 3D joint positions per hand, following the MS COCO convention. Ego-Exo4D has advanced the research in ego-exo video analysis and 3D pose estimation from egocentric perspectives.

3 3D Egocentric Pose Estimation Methods

In this section, we discuss and review different egocentric pose estimation techniques by classifying them into two categories, namely skeletal and model based approaches. Skeletal-based 3D pose estimation methods [33, 34, 35] leverage the human skeleton's representation to accurately track and infer 3D joint position and body movements. Model based human body pose estimation utilizes a parametric model to accurately predict and estimate 3D joint locations and articulations from 2D image data, facilitating versatile and realistic pose estimation across diverse body shapes and poses. There has been a growing interest towards 3D mesh recovery of human bodies [36, 37, 38] especially after the release of SMPL [39] and SMPL-X [31] models. The retrieval of human body meshes is pivotal in supporting subsequent tasks like reconstructing clothed humans [40, 41], rendering [42], and modeling avatars [43, 44]. The sub-sections below expand on the different methods in each category. We have further sub-categorized the methods based on some significant features, as highlighted in bold.

3.1 Skeletal Based Methods

In this section, we have provided details on the skeletal based egocentric pose estimation methods. A brief overview of skeletal based methods has been highlighted in Table 2.

Rhodin et al. [21] pioneered a **marker-less** egocentric motion capture system leveraging a lightweight stereo pair of fisheye cameras integrated into a helmet or virtual reality headset. Their technique utilized a generative pose estimation framework for fisheye views, incorporating a ConvNet-based bodypart detector. This method proved especially beneficial for virtual reality applications that require unrestricted movement and interaction while displaying a fully motion-captured virtual body. However, real-time execution was not achieved with this approach.

To solve the egocentric 3D pose estimation problem in **real-time**, Mo²Cap²[22] employed a two-scale location invariant convolutional network to detect 2D joints, accounting for perspective and radial distortions. It then utilized a location-sensitive distance module to estimate absolute camera-to-joint distances. Actual joint positions were recovered by back-projecting 2D detections, considering distance estimations and fisheye lens properties. This approach guaranteed accurate 3D pose estimation and precise 2D overlay of results. But, their

method failed dramatically for scenes with severe occlusions.

Several methods [25, 19, 45] have tried to account for this occlusion problem. *EgoGlass* [25] addressed a solution for low-visible joints. They proposed a solution that utilizes body part information for enhanced pose detection, particularly in occlusion scenarios. The 2D module includes branches for 2D heatmap and body part information prediction. The 3D module uses a pseudo-limb mask concept to address occlusion challenges in real-world images. The 3D module also serves as an autoencoder for joint heatmaps, aiming to achieve robust 3D body pose estimation and encoding uncertainty in 2D predictions from multiple views. [19] also worked with problems like highly occluded region, closely interacting with the scene in egocentric pose estimation. The proposed method introduces an egocentric depth estimation network for predicting scene depth maps behind the human body using a wide-view egocentric fisheye camera, addressing occlusion caused by the human body through a depth-inpainting network. Additionally, a scene-aware pose estimation network was presented for 3D pose regression. [45] utilized a Vector Quantized-Variational AutoEncoder (VQ-VAE) to predict and optimize human pose, addressing the challenge of obscured lower body appearance in egocentric views. By leveraging a codebook learned from extensive human pose datasets, the method significantly improved generalization performance.

xR-EgoPose [24], an innovative encoder-decoder architecture was introduced to enhance accuracy considering the **differences in resolution between upper body and lower body**. This model addresses resolution differences in upper and lower body poses from monocular images captured by VR headset cameras. The dual-branch decoder handled uncertainties in 2D joint locations by first generating 2D heatmaps and then using an autoencoder to regress 3D poses. However, this method struggles when hands fall outside the camera's range.

To solve this problem of out-of-field-view, [46] developed a method aiming to infer the invisible pose of a person in egocentric videos using dynamic motion signatures and static scene structures. By combining short-term and longerterm pose dynamics, the method utilizes classifiers to estimate pose probabilities and performs joint inference for a longer sequence. In 2021, they extended the idea by proposing another novel technique [54] utilizing both dynamic motion information from camera SLAM and occasionally visible body parts for robust ego pose estimation. It considers the joint estimation of head and body pose, ensuring geometrical consistency and leveraging global coordinate information from camera SLAM. It solves the problem by optimizing the combination of motion and visible shape features. Moreover, EgoTAP [55] addresses out-of-view limbs and self-occlusion issues in stereo egocentric 3D pose estimation by introducing a Grid ViT Heatmap Encoder and Propagation Network. The Grid ViT efficiently summarizes joint heatmaps, preserving spatial relationships crucial for accurate feature embedding. The Propagation Network utilizes skeletal information to predict 3D poses, improving accuracy for both visible and less visible joints.

Scarcity of **real-world dataset** from egocentric view was a major problem which implicates failure for different proposed

Skeletal Methods	Year	Highlighted features	Dataset	Evaluation Metrics
Egocap [21]	2016	First marker-less motion capture system; utilized pose estimation framework for fisheye views with a ConvNet-based body-part detector.	EgoCap	PCK
Jiang et al. [46]	2017	Leveraged dynamic motion signatures and static scene structures to infer the invisible pose efficiently.	custom dataset by Kinect V2 sensor	MPJPE
Mo ² Cap ² [22]	2019	Real-time; disentangled 3D pose estimation, addressed 2D joint detection, camera-to-joint distances, and joint position recovery for accurate results and a precise 2D overlay. MPJPE MPJPE		МРЈРЕ
EgoGlass [25]	2021	Utilized body part information for low-visible joints and tackling self- occlusion by preserving uncertainty information.	EgoGlass	MPJPE, P-MPJPE
xr-EgoPose [24]	2019	Encoder-decoder model for VR headset images, addressing resolution differences in upper and lower body poses, with a dual-branch decoder preserving uncertainty information.	xR-EgoPose	МРЈРЕ
You2Me [47]	2020	Implied interactions with a visible second person, utilizing dyadic interac- tions and incorporating dynamic first-person motion features, static scene features along with explicit second-person body pose interactions for robust pose inference.	You2Me	МРЈРЕ.
Zhang et al. [48]	2021	Incorporated an automatic calibration module with self-correction to alleviate image distortions in fisheye cameras, ensuring consistency between 3D predictions and distorted 2D poses for enhanced accuracy.	xR-EgoPose	МРЈРЕ
Wang et al. [20]	2021	Spatio-temporal optimization framework that combines 2D and 3D key- points, VAE-based motion priors, and SLAM-based camera pose estima- tion, achieving accurate and stable global body pose estimation in egocentric videos.	Mo ² Cap ² , AMASS	PA-MPJPE, BA-MPJPE and Global MPJPE
Wang et al. [18]	2022	Employed weak supervision from an external view, leveraging a spatio- temporal optimization technique, and utilized synthetic data with domain adaptation for improved egocentric human pose estimation.	EgoPW	PA-MPJPE, BA-MPJPE
Akada et al. [17]	2022	Enhances 3D pose estimation by integrating a stereo-based 2D joint location estimation module with weight-sharing encoders and a multi-branch autoencoder for uncertainty capture.	UnrealEgo	MPJPE, PA-MPJPE
Ego+X [49]	2022	dual-camera framework for 3D global pose estimation and social interaction characterization, leveraging visual SLAM and a Pose Refine Module (PRM) for spatial and temporal accuracy and characterizes social interactions based on global 3D human poses.		MPJPE, PA-MPJPE and Bn-MPJPE
Wang et al. [19]	2023	First scene-aware egocentric pose estimation framework utilizing a depth estimation network to handle occluded regions and close interactions.	EgoGTA, EgoPW- Scene	MPJPE, PA-MPJPE
EgoFish3D [27]	2023	A self-supervised framework for egocentric 3D pose estimation, utilizing real-world data with three key modules: third person view, egocentric, and interactive modules, achieving accurate results without the need for ground truth annotations.	ECHP	MPJPE, PA-MPJPE and BA- MPJPE
Ego3DPose [50]	2023	A stereo matcher network and perspective embedding heatmap representa- tion, enhancing accuracy through independent learning of stereo correspon- dences and leveraging 3D perspective information.	UnrealEgo	МРЈРЕ, РА-МРЈРЕ
Ego-STAN [51]	2023	Tackles fisheye distortion and self-occlusions in egocentric human pose estimation through a domain-guided spatio-temporal transformer, using 2D image representations, feature map tokens, and 3D pose estimation for accurate joint localization and uncertainty management.	xr-EgoPose	МРЈРЕ
Dhamanaskar et al. [28]	2023	Utilized third-person view information, creating a self-supervised neural network that establishes a shared space for consistent 3D body pose detection across diverse video settings, ensuring adaptability to real-world scenarios with unknown camera configurations.	First2Third-Pose	МРЈРЕ
EgoFormer [52]	2023	Leveraged video context and establishing long-term temporal relationships. It addresses ambiguity in first-person videos, surpassing dynamic features, and introduces a novel motion clue representation for enhanced accuracy.	CMU Mocap [53]	МРЈРЕ, МРЈАЕ.

Table 2. Popular skeletal based egocentric 3D pose estimation methods.

methods. To account for this problem, [18] proposed a novel method focusing on enhancing egocentric human pose estimation with weak supervision from an external view. The method introduces a spatio-temporal optimization technique to generate accurate 3D poses for frames in the EgoPW dataset, utilizing them as pseudo labels for training an egocentric pose estimation network. A novel learning strategy is employed to supervise egocentric features with high-quality features from a pretrained external view pose estimation model. It further leverages a synthetic dataset and adopts domain adaptation to minimize the gap between synthetic and real data. [17] also proposed a solution for egocentric pose estimation in an unconstrained environment. They came up with a novel technique to enhance 3D pose estimation by employing a 2D joint location estimation module for stereo inputs. The module utilizes weight-sharing encoders and a decoder leveraging stereo information to boost performance. The 3D module comprises a multi-branch autoencoder, predicting 2D heatmaps to generate 3D pose and reconstructing heatmaps to capture uncertainty.

Perspective distortion is an important problem to consider in egocentric 3D pose estimation as it can cause issues like scale variation, depth ambiguity and limited field of view. To enhance accuracy by tackling this problem, *Ego3DPose* [50] introduces a Stereo Matcher network that independently learns stereo correspondences and predicts explicit 3D orientation for each limb, avoiding dependence on full-body information. Additionally, a Perspective Embedding Heatmap representation is introduced, allowing the 2D module to extract and utilize 3D perspective information. [51] also addressed the challenges of **fisheye distortion** and **self-occlusions** in egocentric human pose estimation by leveraging a domain-guided spatio-temporal transformer model, *Ego-STAN*. It utilizes 2D image representations and spatiotemporal attention to mitigate distortions and accurately estimate the location of heavily oc-

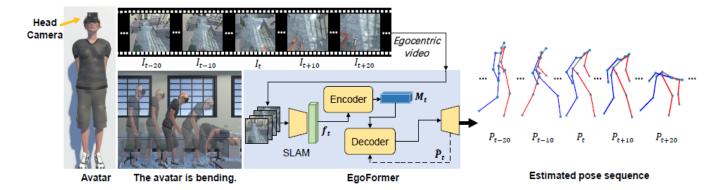


Figure 3. Illustration of a skeletal model for egocentric 3D pose estimation framework. [52]. It utilizes egocentric videos from a front-facing camera to estimate 3D human pose. Left: An avatar with a head-mounted camera captures synchronized video while performing actions. Right: Output pose sequence generated by EgoFormer.

cluded joints. Introducing a spatial concept called feature map tokens (FMT), it draws complex spatio-temporal information from egocentric videos. The model includes a heatmap reconstruction module using deconvolutions, enabling accurate 3D joint coordinate estimation. [48] employed an **automatic calibration** module with self-correction to mitigate the impact of **image distortions** on 3D pose estimation. It estimates intrinsic and distortion camera parameters. Unlike traditional post-processing steps, this module ensures consistency between 3D predictions and distorted 2D poses, effectively alleviating the effects of distortions on 3D pose estimation.

When the predicted poses are in the fisheye camera's local coordinate system instead of the global world coordinate system, it can cause issues like temporal instability. To solve this issue, [20] aimed to estimate accurate and temporally stable global body poses. It employs a spatio-temporal optimization framework, leveraging 2D and 3D keypoints from CNN detection and VAE-based motion priors learned from a mocap dataset. The method addresses challenges like temporal jitters, tracking failures, and unrealistic motions in egocentric pose estimation, by combining local pose estimation, sequential VAEs for motion priors, and SLAM-based camera pose estimation. The method enhances the accuracy and stability in obtaining globally coherent body poses from video sequences. Moreover, Ego+X [49] also proposed a novel egocentric vision framework with two cameras for 3D global pose estimation and social interaction characterization. They proposed Ego-Glo which solves spatial and temporal errors by estimating 3D canonical human pose using a dual-branch network and visual SLAM. Also, their Ego-Soc module performs egocentric social interaction characterization, including object detection and humanhuman interaction, based on the global 3D human poses.

Generating **3D ground truth** data using motion capture system is a cumbersome task. To alleviate this problem, a simple and effective framework, *EgoFish3D* [27] was introduced for egocentric pose estimation using real-world data and self-supervised learning technique. The proposed method introduces three modules for egocentric 3D pose estimation: a third person view module generating accurate 3D poses from

external camera images, an egocentric module predicting 3D poses from a single fisheye image in a self-supervised manner, and an interactive module estimating rotation differences between third person and egocentric views. The method achieves self-supervised egocentric 3D pose estimation without ground truth annotations, utilizing a real-world dataset (ECHP) with synchronized third person and egocentric images.

Yuan et al. [56] introduced a reinforcement learning-based PD control policy for 3D human pose estimation and forecasting from egocentric videos. It learns directly from diverse motion capture data, forecasting stable future motions using a video-conditioned recurrent control technique. Introducing a fail-safe mechanism, their approach outperforms previous methods in controlled and in-the-wild scenarios.

Recent research shows that **linking first-person and third-person view** [70, 71, 72] plays a crucial role for better understanding wearer's action and poses. [73] developed a novel method to make 3D body pose detectors for first-person videos more reliable. They used visual information from paired third-person videos to create a shared space where different views of the same pose are close together. They trained a special neural network to learn this shared space in a self-supervised manner, teaching it to distinguish if two views show the same 3D skeleton. This approach doesn't need adaptation to work with new, unpaired videos, making it suitable for real-world situations where camera settings are unknown.

You2Me [47] addressed the challenge of estimating the 3D body pose of the camera wearer by leveraging interactions with a **visible second person**. The key insight is that dyadic interactions between individuals help to learn temporal models for interlinked poses even when one person is largely **out of the field view**. The method incorporates dynamic first-person motion features, static first-person scene features and second-person's body pose interaction features to explicitly account for the body pose of the camera wearer.

EgoFormer [52], a tansformer-based model for ego-pose estimation in AR and VR applications, addresses the ambiguity in first-person videos by leveraging video context and establishing long-term temporal relationships. EgoFormer extracts

Model Based	Year	Highlighted features	Dataset	Evaluation Metrics
Methods				
Yuan et al. [57]	2018	Integrates control-based modeling, physics simulation, and imitation learning for ego-pose estimation, enabling domain adaptation by considering underlying physics dynamics.	CMU Mocap [53]	MPJPE, MPJVE
Dittadi et al. [58]	2021	Variational autoencoders for generating human body poses from limited head and hand pose data, addressing challenges through specialized inference models.	AMASS	MPJPE, MPJVE
CoolMoves [59]	2021	Achieves real-time, expressive full-body motion synthesis for avatars using limited input cues, dynamically fusing stylized examples from skilled performers, excelling in activities like dancing and fighting.	CMU MoCap	MPJPE, Pearson's correlation coefficient
EgoRenderer [60]	2021	Renders full-body neural avatars from egocentric fisheye camera images for tex- ture synthesis, pose construction, and neural image translation, addressing chal- lenges of top-down view and distortions.	EgoRenderer	SSIM, LPIPS, PSNR
HPS [61]	2021	Integrates wearable sensors, IMUs, and a head-mounted camera to accurately track 3D human poses in pre-scanned environments, achieving drift-free motion estimation through fusion of localization and scene constraints.	HPS	Bidirectional Chamfer Distance
Avatarposer [62]	2022	First learning-based method predicting full-body poses in world coordinates, leveraging transformer encoder, motion input from head and hands, and decoupling global motion for accurate pose estimation.	CMU, AMASS	MPJPE, MPJRE, MPJVE
FLAG [63]	2022	Flow-based model for realistic 3D human body pose prediction with uncertainty estimates, enhancing prior work through high-quality pose generation and efficient latent variable sampling for optimization.	AMASS	МРЈРЕ
EgoEgo [64]	2023	Ego body pose estimation using ego head pose estimation leveraging SLAM, and conditional diffusion for disentangled head and body pose estimation.	ARES	Head Orientation Error, Head Translation Error, MPJPE.
EgoHMR [65]	2023	Scene-conditioned diffusion approach guided by a physics-based collision score, enabling realistic human-scene interactions and accurate estimations for visible body parts while enhancing diversity.	EgoBody	MPJPE, Vertex-to-Vertex errors
EgoPoser [66]	2023	Used sparse motion sensor; mitigates overfitting with position-invariant prediction, adaptable to diverse body sizes, robust with hands out of view and reduces motion artifacts.	AMASS subset [67]	MPJPE, MPJVE
Su et al. [68]	2022	A data framework transforms raw video into 3D pose, enriched by a lightweight Self-Perception Excitation (SPE) module for egocentric self-awareness.	Mocap dataset [56]	MPJPE, MRLE.
SimpleEgo [69]	2024	Directly predicts joint rotations as matrix Fisher distributions, providing robust uncertainty estimation and realistic deployment prospects.	SynthEgo	MPJPE, PA-MPJPE

Table 3. Popular model shape generation based egocentric 3D pose estimation models.

effective temporal features, surpassing dynamic features, and introduces a novel representation for motion clues. Figure 3 shows the proposed architecture for the EgoFormer method.

3.2 Model Based Methods

In this section, we expand on the different model based egocentric pose estimation methods, overview of which is provided in Table 3.

Dittadi et al. [58] introduced a method using variational autoencoders to generate human body poses from **noisy head and hand pose data**. It addresses the challenge of predicting full body poses with limited information by training specialized inference models. The approach involves pre-training a regular VAE with full body poses, followed by optimizing the model using incomplete information. Despite limitations in walking motion representation and assumptions about hand signals, the method proves effective in reconstructing plausible body poses.

Yuan et al. [57] proposed a novel approach employing control-based modeling with physics simulation and utilizes imitation learning to acquire a video-conditioned control policy for ego-pose estimation. Traditional computer vision methods focus solely on motion kinematics [74] neglecting the underlying physics of dynamics [75]. Taking this into account, this framework allows domain adaptation, transferring the policy from simulation to real-world data.

CoolMoves [59], a pioneering Virtual Reality (VR) system, has achieved real-time, expressive full-body motion synthesis for a user's avatar using limited input cues from VR systems. It delineates the movements more prominent through dynamic

fusion with stylized examples from skilled performers. The system excels in synthesizing upper and lower-body motions without explicit tracking cues, addressing challenges in activities like dancing and fighting.

To solve the problem of **top-down view distortions**, *EgoRenderer* [60] offered a novel method tackling the complexities of rendering full-body avatars from egocentric images by decomposing the process into texture synthesis, pose construction, and neural image translation [76, 77]. They introduced a neural network for dense correspondence and texture extraction, and an implicit texture stack for capturing dynamic appearance variations. The approach involves estimating body pose and synthesizing a free-viewpoint pose image, and using a neural image translation network to combine it with textures.

The Human POSEitioning System (HPS) [61] combines wearable sensors, IMUs, and a head-mounted camera to accurately track and integrate 3D human poses within pre-scanned environments. By fusing camera-based localization with IMU-based tracking and scene constraints, HPS achieves drift-free, physically plausible motion estimation.

To address challenges like **body truncation** and **pose ambiguities**, [65] proposed a human mesh recovery model. It introduces a scene-conditioned diffusion model guided by a physics-based collision score, facilitating the generation of realistic human-scene interactions. It utilizes classifier-free training for flexibility in sampling, providing accurate estimations for visible body parts and diverse results for unseen parts.

Jiang et al. [62] developed a pioneering learning-based approach that predicts full-body poses in world coordinates solely from motion input derived from the user's head and hands.

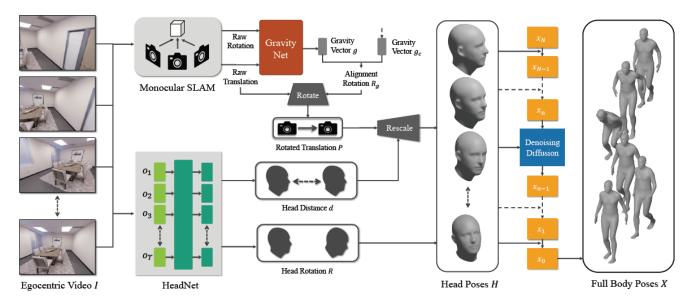


Figure 4. An example of human model generation based egocentric pose estimation framework [64]. The model processes egocentric video to predict head pose using a hybrid approach merging monocular SLAM, GravityNet, and HeadNet. Predicted head pose guides a conditional diffusion model for full-body pose generation.

Leveraging a transformer encoder, the method extracts deep features, distinguishing global motion from local joint orientations to facilitate pose estimation.

FLAG [63] generates realistic 3D human body poses in mixed reality applications using sparse input signals from head mounted devices. It employs a flow-based generative model to predict full-body poses and provides uncertainty estimates for joints. It enhances prior work by generating high-quality poses from limited data and enabling efficient sampling of latent variables for pose generation and optimization.

Su et al. [68] proposed a novel method to estimate 3D wearer poses from egocentric video, overcoming challenges of **body invisibility and complex motion.** The approach involves a data processing framework converting raw video to 3D pose, incorporating a lightweight Self-Perception Excitation (SPE) module for self-understanding from egocentric view.

EgoEgo [64] was introduces for 3D human motion estimation from monocular egocentric videos. The method, as shown in Figure 4, estimates ego-head pose and generates ego-body pose, allowing independent learning without paired datasets. It combines monocular SLAM and transformer-based models for accurate ego-head pose estimation, employing a conditional diffusion model for full-body pose generation based on the predicted head pose. The innovation lies in leveraging head motion as an intermediate representation, enabling the use of diverse datasets effectively.

Cuevas-Velasquez et al. proposed *SimpleEgo* [69] which is a novel approach for regression of probabilistic full-body pose parameters from head-mounted camera images. It directly predicts joint rotations, eliminating the need for iterative fitting processes or manual tuning. By representing joint rotations as matrix Fisher distributions, the model predicts confidence scores, allowing for robust uncertainty estimation. The contributions include probabilistic joint rotation prediction, in-depth

uncertainty analysis, and a prospect of real-world deployment.

EgoPoser [66], a novel approach introduced for full-body pose estimation using sparse motion sensors, focusing on HMD-based ego-body pose estimation in large scenes. It addresses overfitting issues in existing methods by emphasizing position-invariant prediction with a Global-in-Local motion decomposition strategy. Notably, EgoPoser adapts to diverse body sizes, remains robust when hands are out of view, and reduces motion artifacts.

4 Evaluation Metrics

Several approaches have been introduced to assess 3D egocentric human pose estimation. In this section, we delve into the evaluation metrics commonly used to assess egocentric pose estimation across different skeletal and model based methods.

MPJPE (Mean Per Joint Position Error): This metric is widely utilized to measure the accuracy of predicted 3D joint positions in comparison to ground truth positions. The calculation of MPJPE involves determining the Euclidean distance between the estimated 3D joints and their corresponding ground truth positions. Mathematically, it is expressed as follows:

$$MPJPE = \frac{1}{N} \sum_{i=1}^{N} \|J_i - J_i^*\|$$
 (1)

Here, N is the total number of joints, J_i denotes the estimated position of the ith joint, J_i^* represents the ground truth position of the ith joint. MPJPE serves as a robust measure to quantify the overall accuracy of 3D pose estimation algorithms across different joints.

PA-MPJPE focuses on the individual pose accuracy by checking the alignment between the estimated pose and the ground truth pose of each frame using Procrustes analysis.

Methods	Walking	Sitting	Crawling	Crouching	Boxing	Dancing	Stretching	Waving	Average
VNect [78]	65.28	129.59	133.08	120.39	78.43	82.46	153.17	83.91	97.85
3DV'17 [79]	48.76	101.22	118.96	94.93	57.34	60.96	111.36	64.50	76.28
EgoFish3D [27]	60.9	42.1	65.0	82.7	79.0	55.5	59.1	94.5	66.8
Zhang et al. [48]	41.16	76.58	73.04	89.67	52.96	58.90	92.21	71.55	62.13
Mo ² Cap ² [22]	38.41	70.94	94.31	81.90	48.55	55.19	99.34	60.92	61.40
xR-egopose [24]	38.39	61.59	69.53	51.14	37.67	42.10	58.32	44.77	48.16
SelfPose-UNet [6]	45.83	47.24	47.35	45.15	48.72	47.00	46.15	46.45	46.61

Table 4. Comparison of different 3D egocentric pose estimation methods on Mo²Cap² dataset using MPJPE (mm).

BA-MPJPE involves resizing bone lengths to a standard skeleton and then calculating Procrustes-aligned MPJPE between the sequences. This metric provides a comprehensive evaluation by considering structural consistency in bone lengths and eliminating body scale influence.

Global MPJPE aligns all poses within a batch to ground truth, considering translation and rotation and evaluates global joint position accuracy.

MPJRE (**Mean Per Joint Rotation Error**) calculates the average rotational disparity between predicted and ground truth joint rotations.

MPJVE (Mean Per Joint Velocity Error) assesses the average velocity difference between predicted and ground truth joint movements.

Percentage of Correct Key-points (PCK) metric is a measure of accuracy that checks if the predicted keypoint and the actual joint are close within a specific distance limit. Typically, this distance threshold is set based on the size of the subject.

Head Orientation Error assesses rotational accuracy in head pose estimation. It measures the angular disparity by calculating the Frobenius norm of the difference between the predicted and ground truth head rotation matrices.

Head Translation Error focuses on translation accuracy. It quantifies the mean Euclidean distance between predicted and ground truth head trajectories, providing a quantitative measure of spatial disparity.

5 Performance Analysis

This section aims to provide a comprehensive evaluation of various egocentric pose estimation methods across multiple datasets. This in-depth analysis is crucial for understanding the versatility and adaptability of these methods in different scenarios. Each dataset may present unique challenges such as varied lighting conditions, backgrounds, and subject movements. We analyze the performance of different state-of-the-art methods for the 3D egocentric human pose estimation on some of these popular egocentric datasets.

5.1 Performance on Mo²Cap² dataset

Mo²Cap² [22] dataset has been widely used in egocentric pose estimation approaches for training and evaluation purpose using the MPJPE metric. The performance of different egocentric pose estimation methods across different actions on this dataset have been depicted in Table 4. The average MPJPE across all actions reduces from 97.85 mm in VNect [78] method to 46.61 mm in SelfPose-UNet [6] method. We see that 2D-3D lifting models [6, 24] achieved better results than direct 3D pose estimation methods. It may be due to the preserved uncertainty information of the joints. The methods evaluated on this dataset do not perform well on the poses where body parts are partially visible or occluded. The Mo²Cap² [22] is a synthetic dataset having a large number of training and testing data. Though the dataset comprises 3000 subject actions and 700 body textures, performance of these methods deteriorates significantly in complex real world scenarios.

5.2 Performance on xr-EgoPose dataset

The xr-EgoPose [24] dataset has a large number of dataset comprising 383k frames but the action class is quite low compared to the Mo²Cap² [22] dataset. It has been extensively used by many state-of-the-art egocentric pose estimation methods for evaluating their models. From Table 5, we see that EgoGlass

Methods	Game	Gest.	Greeting	Lower	Pat	React	Talk	Upper	Walk	All
				Stretch				Stretch		
Martinez et al.[80]	109.6	105.4	119.3	125.8	93.0	119.7	111.1	124.5	130.5	122.1
xR-egopose [24]	56.0	50.2	44.6	51.5	59.4	60.8	43.9	53.9	57.7	58.2
SelfPose [6]	60.4	54.6	44.7	56.5	57.7	52.7	56.4	53.6	55.4	54.7
Zhang et al. [48]	36.8	34.1	36.7	50.1	57.2	34.4	32.8	54.3	52.6	50.0
EgoFish3D [27]	48.0	48.2	42.5	47.3	48.8	53.6	47.2	36.2	48.9	46.1
Ego-STAN [51]	33.1	31.6	36.9	38.9	29.2	29.6	29.7	44.3	40.9	40.4
EgoGlass [25]	32.8	30.5	33.7	35.5	45.7	33.2	27.0	40.1	37.4	37.7

Table 5. Comparison of different 3D egocentric pose estimation methods on xr-EgoPose dataset using MPJPE (mm).

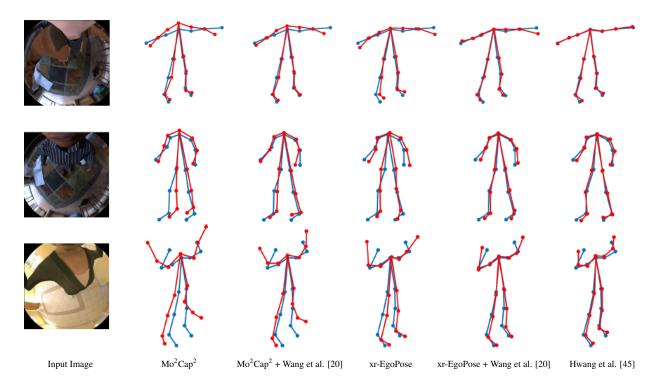


Figure 5. Qualitative comparison between different state-of-the-art egocentric 3D pose estimation models on xr-EgoPose dataset [24]. The predicted 3D poses (highlighted in red) are superimposed onto the ground truth poses (depicted in blue).

[25] outperforms all the existing methods in terms of mean joint error. It may be Sdue to utilizing body part information for low visible joints. Figure 5 demonstrates a visual representation of 3D pose generated by different state-of-the-art egocentric 3D pose estimation models from same egocentric inputs from xr-EgoPose dataset [24]. The mean joint error is less than the methods on Mo²Cap² [22] dataset for actions with less visible joints. But, in this dataset, most of the actions that are used for evaluation are quite simple and conspicuous. Due to this, these actions may not be a proper benchmark to evaluate the 3D pose estimation from egocentric view.

5.3 Performance on other datasets

Apart from the mentioned datasets, there also exists some noteworthy datasets which have been used for evaluation in egocentric pose estimation. Table 6 and Table 7 depicts the results of different methods in UnrealEgo [17] and Wang et al.'s [20] dataset demonstrating MPJPE and PA-MPJPE. We can see that methods on UnrealEgo [17] dataset perform comparatively better than the methods evaluated on Wang et al.'s [20] dataset. It is due to 17 different action in diversified environments with a large amount of indoor and outdoor scenes in UnrealEgo [17] dataset whereas Wang et al.'s [20] dataset contains few classified actions and scenes. From the results in the mentioned tables, we observe that xr-EgoPose [24] performs worse in both the datasets. This maybe due to the evaluating datasets being real world whereas xr-EgoPose [24] is trained in synthetic dataset. Camera setup can also be an issue in this case because this method fails significantly in the out-of-field view.

Moreover, datasets like ECHA, EgoGlass, EgoCap etc. have also been used by various egocentric pose estimation models for evaluation and ablation study purpose. In summary, the performance evaluation section provides valuable insights into the efficacy of various egocentric pose estimation methods across diverse datasets.

Methods	MPJPE	PA-MPJPE
xR-egopose [24]	112.86	88.71
EgoGlass [25]	86.45	63.71
UnrealEgo [17]	79.06	59.95
Ego3DPose [50]	60.82	48.47
Akada et al. [30]	50.55	40.50
EgoTap [55]	41.06	35.39

Table 6. Comparison of 3D Egocentric Pose Estimation methods on UnrealEgo [17] dataset.

Methods	MPJPE	PA-MPJPE
xR-egopose [24]	112.0	87.20
Mo ² Cap ² [22]	102.3	74.46
Rhodin et al. [81]	89.67	73.56
EgoPW [18]	81.71	64.87
Scene Aware [19]	76.50	61.92

Table 7. Comparison of 3D Egocentric Pose Estimation methods on Wang et al.'s [20] dataset.

6 Discussion and Future Directions

In this survey paper, we provide a systematic overview of 3D egocentric human pose estimation, encompassing diverse datasets and estimation methodologies. We highlight recent studies addressing the challenge of estimating 3D human pose from an egocentric viewpoint using RGB images or video sequences, an area that remains relatively under-explored in research. Consequently, researchers have recently proposed diverse datasets with lightweight setups. However, the absence of standardized **benchmark datasets** poses a challenge for evaluating the robustness of different egocentric pose estimation models. Recent advancements, especially by the introduction of Ego-Exo4D [29], offers promise as a valuable resource to address this research gap.

We provide a systematic overview of several skeletal and model based methods for egocentric pose estimation, along with a discussion of their individual strengths and weaknesses. We realize that most of the existing methods encounter difficulties for pose estimation in case of **in-the-wild scenarios**. This is primarily due to insufficient in-the-wild training data which affects the generalization ability of different egocentric pose estimation models. Notably, similar to traditional pose estimation, the biggest challenges of egocentric pose estimation models are strong occlusions and limited field of view, especially for the lower body joints. Multi view consistency may help to to solve this using additional 3D information. Moreover, temporal and contextual information can be utilized further to improve the robustness of the models considering these issues. Consequently, there exists ample scope for refining egocentric pose estimation approaches to better suit real-time XRtechnologies.

In conclusion, this survey paper serves as a comprehensive resource for researchers seeking to explore the existing egocentric pose estimation methods, understand prevalent challenges, and make further advancements in this important field.

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