End-to-End Workflow for Finite Element Accident Reconstruction: coupling Video-Based Human Pose Estimation with HBM Personalisation and Positioning

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I. INTRODUCTION

Head injuries in sports and in traffic accidents are major public health concerns, highlighting the need for enhanced prevention strategies [1-2]. Finite Element (FE) modeling is essential for this analysis, yet its effectiveness is limited by the accuracy of 3D kinematic inputs, often challenged by single-view video analyses. The Skinned Multi-Person Linear (SMPL) model, capable of generating detailed 3D human body representations, addresses this limitation by optimising precise posture and body shape parameters, which has the potential to improve the accuracy for FE modeling [3]. Despite SMPL's capabilities, current studies often use standard Human Body Models (HBMs), neglecting the impact of body shape on reconstruction accuracy. In one of our research initiatives, we have addressed this by employing full-body HBM morphing using the SMPL model to incorporate subject-specific variations [4]. Validation studies have confirmed the efficacy of using SMPL in estimating kinematics and postures from single-view scenarios [5], and further research has shown promising correlations between SMPL-informed FE simulation and medical diagnoses of accidents [6]. However, a gap in video analysis and FE prediction accuracy persists, highlighting the need for an integrated approach to improve HBM refinement for accurate reconstructions. This study presents a comprehensive workflow with the potential to contribute to accident reconstruction standards, aiming to refine injury reconstruction accuracy and support enhanced safety and preventative strategies in sports and traffic environments.

II. METHODS

SMPL(X)-based pose estimation account for body measurement

Figure 1 outlines our accident reconstruction workflow. Using the subject's anthropometric data (primarily height and weight) obtained from public sources, we employ the SMPLX regressor to determine the top ten principal components of body shape (β), fixing them for consistency. Pose analysis begins with YOLO network detection in the accident scene, followed by OpenPose extracting 2D keypoints from the cropped image [5]. These keypoints with the image via SMPLify [7] estimate the initial posture (θ), which is further refined to a subject-specific posture (θ') using the fixed β values, leading to the generation of a subject-specific SMPLX mesh and the regression of 3D joint centres.

Skeletal details derived from the SMPL model aid in both morphing and HBM positioning, accomplished through model transfer and OSSO model [8]. This process is also applied to generate the subject in a neutral standing posture, for ease of the morphing step from a generic HBM to subject-specific HBM.

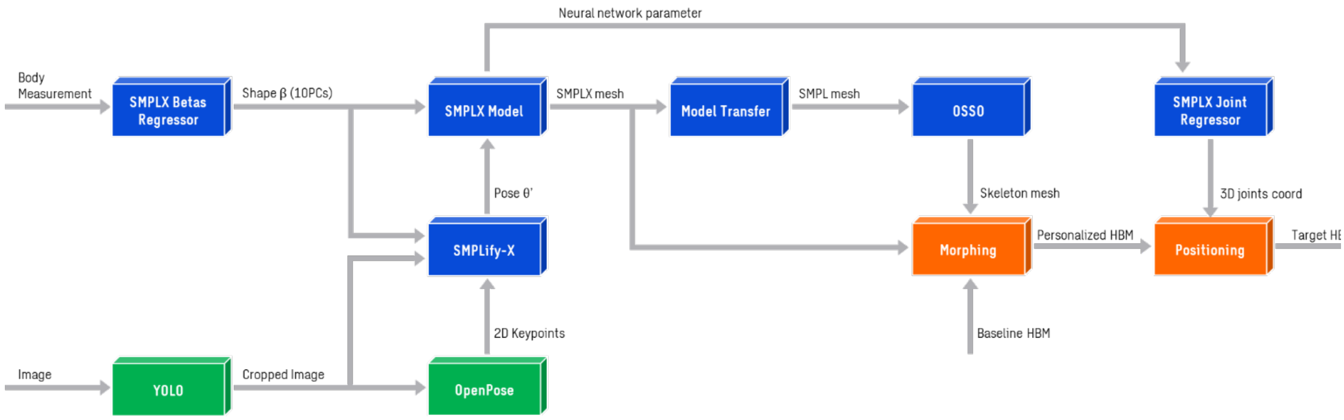

Fig. 1. Overview of the integrated pipeline for 3D human pose estimation and HBM personalisation in accident reconstruction simulations.

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HBM personalised morphing and positioning

The THUMS v4.02 model is morphed with subject-specific SMPLX and OSSO meshes, reflecting skin and skeleton details in a standing posture. Image registration [4] creates a displacement field, morphing the HBM mesh with SMPLX-derived geometries and ensuring the model's fidelity to the subject's anatomy. Positioning of the HBM is achieved through simulations using Marionette technique [8], where we developed an in-house algorithm specifically for this purpose. This algorithm places cable nodes at the 3D joint centres as identified by the SMPLX model. Each cable is then connected at one end to these nodes and at the other end to the corresponding anatomical nodes on the HBM. Through this simulation, the HBM is pulled to align with the posture depicted in the video, ensuring a faithful representation of the accident scenario.

III. INITIAL FINDINGS

Using a public NFL game video as demonstration, we analyse the preceding frame of a confirmed concussion incident, focusing on the left player. The 2D joints detection from OpenPose is depicted in Fig. 2(a). Figure 2(b) includes the SMPLX-generated skin mesh in a transparent gray overlay and the OSSO-derived skeleton mesh in blue, capturing the player's dynamic posture alongside personalised body shape details. Figure 2(c) presents the setup of our simulation, illustrating the placement of cables that extend from the morphed, standing HBM to the target joint coordinates as determined by the SMPLX model. The final positioned HBM, reflecting the player's posture at the moment of collision, is displayed in Fig. 2(d), providing a representation that captures the essence of the incident within the context of the simulation's configurations.

(a) (b) (c) (d)

Fig. 2. Illustration of the accident reconstruction process for an NFL concussion incident: (a) 2D joint detection overlay on the player; (b) SMPLX skin and OSSO skeleton meshes depicting personalised posture; (c) simulation setup with cable connections; and (d) the final positioned HBM aligned with the player's collision posture.

IV. DISCUSSION

In this study, we propose a comprehensive pipeline-integrating, video-based 3D human pose estimation with FE personalisation and positioning, aiming to enhance the precision of accident reconstruction simulations. By employing advanced computer vision techniques, we address the challenge of aligning the HBM with observed postures in real-world scenarios, as demonstrated in our analysis of an NFL concussion case. These preliminary results show the potential of our proposed pipeline in establishing FE simulations, demonstrating robustness even under the constraints of suboptimal viewpoints and image quality.

V. REFERENCES

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