Kinematic Motion Analysis with Volumetric Motion Capture

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***Abstract*—Kinematic motion analysis is widely used in healthcare, sports medicine, robotics, biomechanics, sports science, etc. Motion capture systems are essential for motion analysis. There are three types of motion capture systems: marker-based capture, vision-based capture, and volumetric capture. Marker-based motion capture systems can achieve fairly accurate results but attaching markers to a body is inconvenient and time-consuming. Vision-based, marker-less motion capture systems are more desirable because of their non-intrusiveness and flexibility. Volumetric capture is a newer and more advanced marker-less motion capture system that can reconstruct realistic, full-body, animated 3D character models. But volumetric capture has rarely been used for motion analysis because volumetric motion data presents new challenges. We propose a new method for conducting kinematic motion analysis using volumetric capture data. This method consists of a three-stage pipeline. First, the motion is captured by a volumetric capture system. Then the volumetric capture data is processed using the Iterative Closest Points (ICP) algorithm to generate virtual markers that track the motion. Third, the motion tracking data is imported into the biomechanical analysis tool OpenSim for kinematic motion analysis. Our motion analysis method enables users to apply numerical motion analysis to the skeleton model in OpenSim while also studying the full-body, animated 3D model from different angles. It has the potential to provide more detailed and in-depth motion analysis for areas such as healthcare, sports science, and biomechanics.**

***Index Terms*—Kinematic Motion Analysis, Volumetric Capture, Motion Capture**

I. INTRODUCTION

Computer-assisted human motion analysis is used in many areas such as healthcare, sports medicine, robotics, biomechanics, sports science, etc. For example, gait analysis can be used to detect motion variations for evaluating the evolution of neurodegenerative diseases [1]. Motion analysis is widely used in sports medicine [2], [3] and sports science [4], [5]. Pose estimation is also an important part of computer vision [6].

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Motion analysis relies on the data from motion capture systems. There are three types of motion capture systems: marker-based systems, vision-based systems, and volumetric capture systems. Marker-based systems (e.g., Optitrack, Vicon, Qualisys) can generate highly accurate motion tracking data [7] but attaching markers to human bodies can be inconvenient and time-consuming.

Vision-based motion capture systems (e.g., Theia, Deepmotion, Captury, Simi) use computer vision to identify motion from images or videos. Since the motion capture subjects do not need to wear markers or any special suits, they can move more naturally, and the vision-based motion capture systems can be used in the field to capture live performances. The main drawback of vision-based motion capture systems is that they are not as accurate as the marker-based systems. But recent advances in computer vision and machine learning, such as OpenPose [8], has led to significant interest in using vision-based motion capture system for motion analysis [6], [9], [10].

Volumetric motion capture systems (e.g., 4DViews, Microsoft Mixed Reality Capture Studios, Sony, EF EVE, Volograms, Tetavi) go a step further than the vision-based systems by generating textured, and animated 3D character models instead of skeleton models [11]. The animated 3D character models provide much more details than the skeleton models and preserve the subtleties of the motions. In addition, the 3D models can be imported into 3D graphics tools such as Maya, Blender, Unity, or Unreal. Therefore, the 3D models can be integrated into simulated 3D environments and viewed from different angles.

Volumetric capture is relatively new and has been primarily used for entertainment, broadcasting, advertisement, etc. Not much work has been done in using volumetric capture for motion analysis. Part of the reason is that volumetric motion capture presents new challenges. Because there are no markers, the locations of the joints need to be calculated from the animated 3D models. Since we are dealing with 3D models, image-based pose recognition technologies, such as OpenPose

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[8], no longer apply. A new method for motion analysis is needed.

In this paper, we propose a new method for conducting kinematic motion analysis using volumetric capture data. This method consists of a three-stage pipeline. First, the motion is captured by a volumetric capture system. Then the volumetric capture data is processed using the Iterative Closest Points (ICP) algorithm [12], [13] to generate virtual markers that track the motion in every time frame. Third, the motion tracking data is imported into the biomechanical analysis tool OpenSim [14], where the motion tracking data is closely fitted with an anatomically correct skeleton model. The motion analysis is conducted using OpenSim's powerful kinematic motion analysis tools.

Our motion analysis method offers unique benefits over marker-based or vision-based motion capture systems. Users can apply numerical motion analysis to the skeleton model in OpenSim while also studying the full-body, animated 3D model from different angles, leading to more detailed and in-depth motion analysis. As volumetric motion capture systems are more widely adopted, this work will benefit many areas that rely on motion capture data for motion analysis, such as healthcare, biomechanics, sports medicine, sports science, etc.

II. Background and Related Work

A. Motion Analysis

Motion analysis can be classified into three categories [1]: spatial-temporal motion analysis, kinematic motion analysis, and kinetic motion analysis. Spatial-temporal analyses focus on the motion's distance, time, and velocity. Commonly used features include step length, stride length, step width, step time, stride time, stance time, swing time, cadence (steps per minute), and step velocity (distance per second). These parameters can be obtained via accelerometers, motion capture systems, or computer vision technologies.

Kinematic motion analyses focus on rotations. The commonly used features include shoulder angle, elbow angle, wrist angle, hip angle, knee angle, pelvic tilt, foot angle, etc. These parameters can be obtained via motion capture systems, computer vision technologies, and gyroscope. Our research focuses on kinematic motion analysis.

Kinetic motion analyses focus on the forces that cause the motion. Commonly used features include arm, hip, or knee extension/flexion moment and power. These parameters can be obtained via force plates, pressure sensors, or instrumented walkways. We do not consider kinetic motion analysis in this study.

B. Motion Capture

Before motion capture systems were invented, motion analysis depended on the manual tracking of motion in images or videos. Manual motion tracking is still occasionally used to provide the ground truth for evaluating motion capture systems. Marker-based motion capture systems (e.g., Optitrack, Vicon, Qualisys) have been around for a long time and have achieved high motion tracking accuracy [4], [7]. They are generally considered the current gold standard for motion tracking and are often used as references for vision-based motion capture systems. In marker-based motion capture systems, specialty cameras or sensors track the motion of markers attached to the motion capture subject. The output is a skeleton model created by connecting these tracked markers. The subjects of motion capture need to wear special suits, and the markers may fall off during the motion capture. The most accurate marker-based motion capture systems are expensive and can only be used in a lab.

Vision-based, marker-less motion capture systems have also been studied for a long time [15], [16]. A typical vision-based motion capture system takes pictures or videos of subjects, generates skeleton models by analyzing the pictures or videos, and often superimposes the skeleton model onto the original picture or video. Various motion analyses can then be conducted with the skeleton model [6], [9], [10], [15]–[19]. Machine learning techniques can be used to identify different poses [6], [10], [20]. In theory, vision-based motion capture systems are more desirable than marker-based systems, but low accuracy and reliability have prevented them from gaining wide adoption. With the rise of machine learning [8] and better camera technologies, the accuracy and reliability of vision-based motion capture systems have improved significantly in recent years and many commercial systems are available, such as Theia, Deepmotion, Captury, and Simi. There have been a number of reviews of recent advances in motion analysis using vision-based motion capture systems [6], [9], [10], [17]–[19].

Volumetric capture (also called volumetric video or performance capture) uses computer vision, computer graphics, and advanced camera technologies to capture a moving character and reconstruct it as an animated 3D model. [11], [21]–[29] As in the vision-based systems, the motion capture subjects can wear normal cloth, without any markers. While other types of motion capture systems generate skeleton models, volumetric capture systems generate either 3D mesh models or point clouds, which can be imported into game engines, 3D animation tools, or other software for display or further processing. In general, commercial volumetric capture systems, such as 4DViews and Microsoft Mixed Reality Capture Studios, use an array of cameras to capture the motions. These systems are expensive and can only be used in a lab. Recently, several free mobile volumetric capture apps (e.g., Volograms, Tetavi) have been released but their performance and feasibility are still unclear.

Volumetric capture is still relatively new. So far, they have primarily been used for entertainment, live broadcasting, film and TV, advertisement, etc. Very little work has been done in using volumetric captures for motion analysis. But volumetric capture provides some advantages over other types of motion capture systems. The 3D models generated by volumetric captures not only preserve the small details of the motions but also allow users to examine the motions from different angles, enabling more in-depth motion analysis. However, volumetric captures also creates new challenges for motion analysis. Since there are no markers, the locations of the joints need to be calculated based on the animated 3D model. Image-based approaches, such as OpenPose [8], no longer apply. There have been some previous works on generating skeleton models from 3D geometry data, which is the reverse problem of 3D skinning. For example, Zhu, et al. [30] proposed a system to reconstruct subject-specific anatomy models from point clouds. Kadlecek, et al. [31] built a template anatomical model of an average male and then developed methods to closely fit the template model to point clouds from 3D scans. These previous works were designed primarily for computer animation. We are solving a similar problem but focusing on kinematic motion analysis. Therefore, we do not need the complicated muscle models in Kadlecek, et al. [31]. Besides, we deal with polygon mesh models rather than point clouds.

III. Methodology

A. Overview

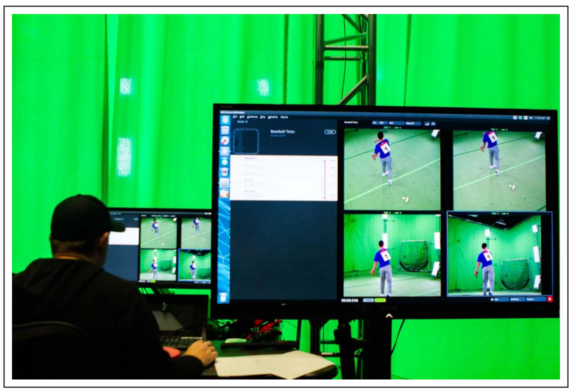

Fig. 1. 4DViews Volumetric Capture Studio at Georgia State University

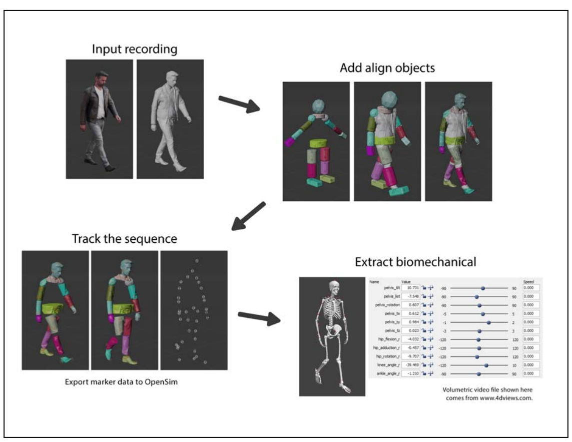

Fig. 2. Overview of the proposed methodology

Our goal is to perform kinematic motion analysis on volumetric motion capture data. This is achieved in three steps. First, the movements of the subject are recorded using the 4DViews Volumetric Capture system (Fig. 1) [32]. The output is an Alembic (.abc) animation file that contains an animated 3D character model.

Second, the animation file is imported into Blender [33]. Using Blender's Python API and the Iterative Closest Point Alignment add-on [34], a program is developed to track the motion of the animated character, generate alignment objects, and calculate virtual marker positions. The output is a Track Row Column (.trc) file that stores the positions of virtual markers at different time steps. This is the same type of file that a marker-based motion capture system would generate.

Third, the marker tracking data is imported into OpenSim [14], an open-source biomechanical analysis software. An anatomical skeleton model from OpenSim is aligned with the imported marker tracking data through inverse kinematics, resulting in an animated skeleton model. With OpenSim's built-in kinematic motion analysis functions, the angles of joint flexion and extension can be calculated and visualized.

Fig. 2 gives an overview of this process. Fig. 3 shows the difference between our method with volumetric capture and motion analyses with other types of motion capture systems.

B. Volumetric Motion Capture

We used the 4DViews volumetric motion capture system [32] in our lab (Fig. 1) to capture the motion. The output of the system is a textured and animated 3D model (or models), which can be stored in either the 4DViews format (.4ds) or the Alembic format (.abc). The 4DViews file can be imported into game engines Unity or Unreal, while the Alembic file can be imported into 3D animation tools such as Maya, Blender, Cinema 4D, etc. In our study, we used the Alembic files.

C. Motion Tracking

Using Blender's Python API and the Iterative Closest Point Alignment add-on [34], a program is developed to track the motion of the animated character. We chose Blender because it is open source and is one of the major 3D modeling and animation tools for processing 4DViews data. Blender's powerful GUI and Python API make it easier to process volumetric capture data than developing a separate program ourselves. Fig. 4 shows the 3D animated model after it is imported into Blender.

Once the volumetric capture data (an Alembic file) is imported into Blender, the program generates a set of alignment objects representative of different body regions. These alignment objects are simple 3D shapes that can be scaled and altered to match the specific motion capture subject (Fig. 5). It requires the up-front manual work of placing the alignment objects onto their respective positions on the body. This is why they are called alignment objects. The initial manual alignment works best for a pose where body parts are not overlapping, and each region is easily defined (such as a T-pose or A-pose). Ideally, the subject would be asked to take one of these poses at the beginning of the recording session. This initial step is the only manual operation in the motion tracking process. The rest of the process is automated.

Utilizing Blender's Boolean operator, the program generates the intersection of the alignment objects and the base mesh, transforming alignment objects to represent their respective

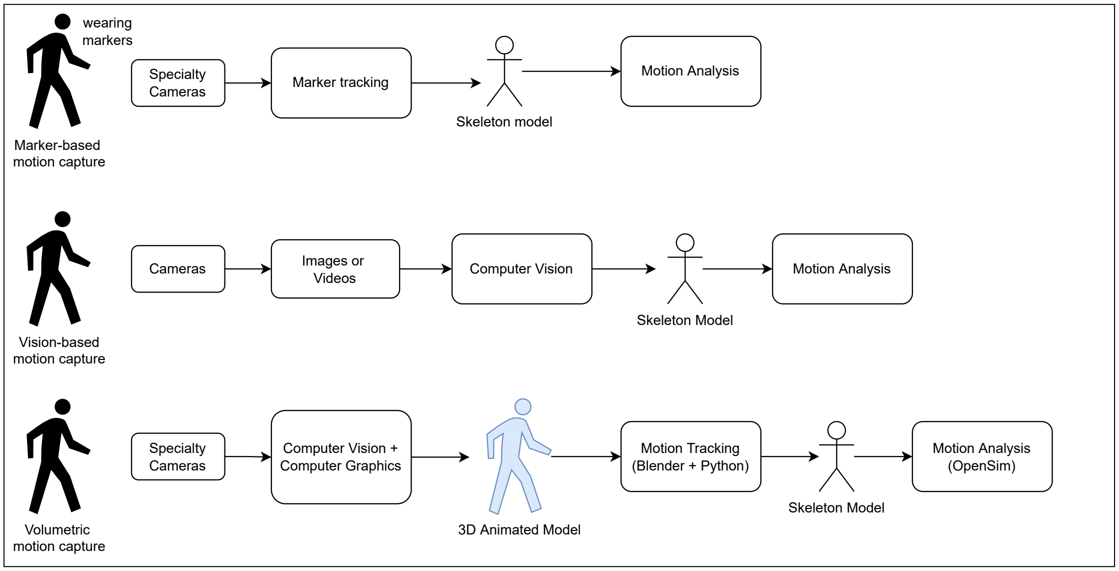

Fig. 3. A comparison of motion analysis using our method (volumetric capture) and the motion analysis using marker-based and vision-based motion capture systems

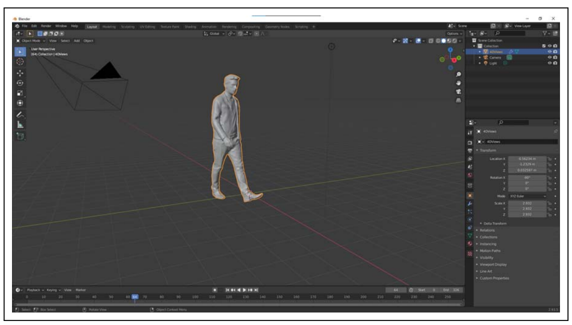

Fig. 4. Importing volumetric capture data into Blender

body parts closely. The next step is to use the program's track forward and track backward features to register each alignment object to the mesh over every frame of the animation. The program does this by using the Iterative Closest Point (ICP) algorithm to register the alignment objects with the mesh [12], [13].

Iterative Closest Point (ICP) algorithm aims to find the transformation that aligns one set of points with a 3D surface or another set of points. Specifically, suppose we have two sets of 3D positions: $X = \{x_1, ..., x_n\}$, $Y = \{y_1, ..., y_n\}$. Each x_i and y_i is a 3D coordinate. We want to find the translation vector t and rotation matrix R that minimizes the sum of the squared error E, where

$$E = \frac{1}{N}\sum_{n=1}^{N}(\|x_i - Ry_i - t\|)^2$$

R and t are calculated as follows. First, make both sets of points centered on the origin by subtracting each point from its center of mass.

$$X' = \{x_i - \frac{1}{N}\sum_{i=1}^{N} x_i\}$$

$$Y' = \{y_i - \frac{1}{N}\sum_{i=1}^{N} y_i\}$$

Then we calculate the singular value decomposition (SVD) of matrix $A = \sum_{i=1}^{N} x_i' y_i'^T$:

$$A = USV^T$$

where S has singular values and is diagonal, and both U and V are orthogonal matrices.

Thus the optimal R and t that minimize E are:

$$R = UV^T$$

$$t = (\frac{1}{N}\sum_{i=1}^{N} x_i - R\frac{1}{N}\sum_{i=1}^{N} y_i)$$

Each alignment object has two to three markers attached to them that are used later in OpenSim. When the alignment objects are generated, the markers are automatically placed in certain default positions, but they can be manually moved if needed to fit the specific subject. As the alignment objects track to the animated mesh via ICP, the markers are animated accordingly. Finally, the positions of the markers throughout the animation sequence are exported to a Track Row Column (.trc) file, just like a marker-based motion capture system would do.

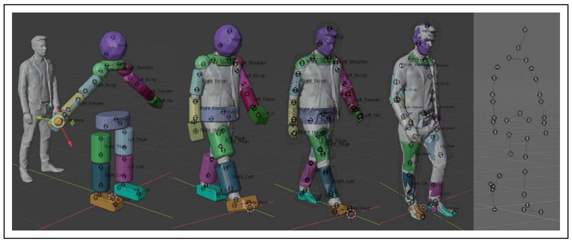

Fig. 5. Motion tracking using the Iterative Closest Point (ICP) algorithm

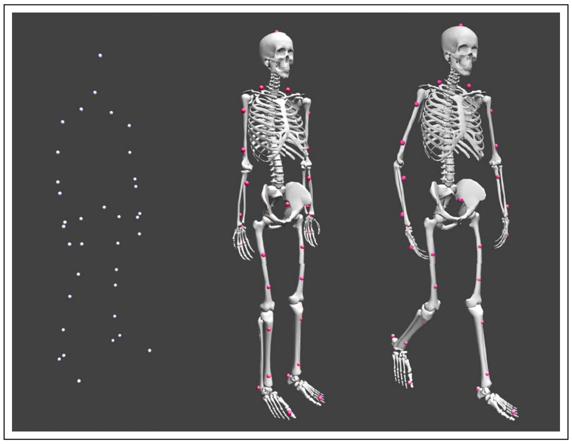

Fig. 6. Animating a skeleton model in OpenSim using volumetric capture data

D. Motion Analysis

OpenSim [14] is an open-source software package for biomechanical motion analysis. The OpenSim GUI provides a user-friendly interface for motion analysis, while the OpenSim API is for coding. OpenSim also provides anatomically correct skeleton and muscle models [35] with controls for the various joint flexions and extensions, with virtual markers already attached to the skeleton model. Since we are only concerned with kinematic motion analysis, the muscle models are not used in this study. When the Track Row Column (.trc) file generated by the previous step is imported into OpenSim, the marker data is automatically synchronized with the markers on the OpenSim's skeleton model using OpenSim's inverse kinematic simulation. Therefore, the skeleton model is automatically scaled to match the recorded subject, and the two sets of markers are synchronized on every frame of the animation, resulting in an animated skeleton model reproducing the captured motion. With OpenSim's powerful kinematic motion analysis tools, the joint movements can be calculated, analyzed, and visualized (Fig. 8).

IV. Case Studies and Discussion

Fig. 7 shows the results of applying our method to two different volumetric captures: walking and exercise routine. Our proposed motion analysis method provides unique benefits over marker-based or vision-based motion capture systems. Using our process, users can apply numerical motion analysis to the skeleton model in OpenSim while studying the animated

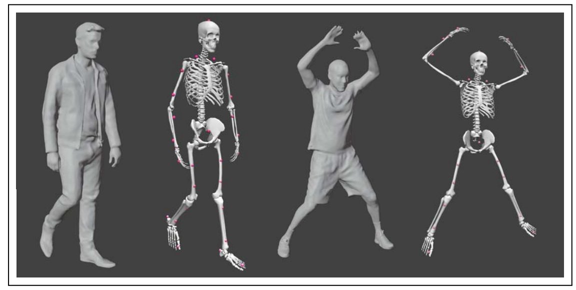

Fig. 7. Motion analysis case studies

3D model from different angles in Blender (or other animation tools). This provides users with a higher level of detail for more in-depth motion analysis.

In general, the system performed better with the walking motion capture (Fig. 7 left), as it consists of smaller movements and minimal deformation. The exercise routine motion capture (Fig. 7 right) contains larger movements, particularly in the arms that swing up and down. Here the system tended to have more difficulty tracking the forearms and in a few situations during the tracking, alignment objects had to be manually re-positioned before resuming tracking. However, both data sets were able to be used in OpenSim to successfully animate the skeleton model as shown in Fig. 7.

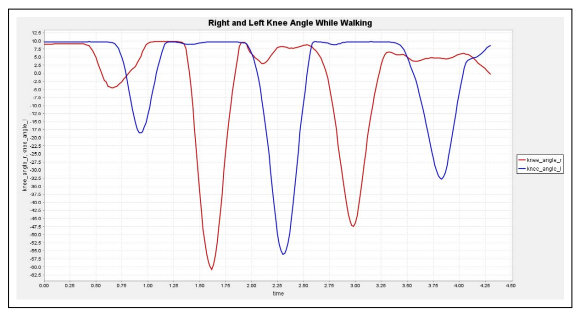

Fig. 8. Rotation angles of the knee joints for the walking volumetric capture

Fig. 8 shows the rotation angle of the subject's knees from the walking motion capture (Fig. 7 left) calculated by OpenSim's kinematic motion analysis tools.

Some of the limitations of this method include the possibility of alignment objects drifting or losing tracking over the sequence. Areas of the body that are less well-defined tend to be harder to track. For example, when the subject's arm is completely straight, the system can have difficulty determining the difference between the forearm and the upper arm. Similarly, large and fast movements can also be difficult to track at times. However, if an alignment object does lose tracking, the user is able to manually realign it and resume automatic tracking. This kind of problem is common among motion capture systems. Even marker-based motion capture systems often require manual data cleaning.

Recordings of subjects with baggy clothing can also be problematic if the clothing often moves and changes shape because it is harder to place the alignment objects and markers.

Again, this type of problem is common for vision-based motion capture systems. Although getting a proper track of the body movements can depend on the quality of the recording and the scope of the subject's movements, in general, the system provides a steady track from which useful data can be extracted.

V. Conclusion and Future Work

We have presented a method for conducting motion analysis with volumetric motion capture data. Volumetric capture is relatively new and provides advantages over marker-based or vision-based motion capture systems because volumetric capture reconstructs full-body motion. However, volumetric capture systems also pose new challenges for motion analysis because traditional methods no longer apply. We propose a three-stage pipeline that extracts motion data from volumetric information. This process allows users to conduct both numerical motion analysis and full-body motion analysis from different angles. In the future, we plan to continue improving the motion tracking accuracy of this method by integrating machine learning methods. We also plan to apply this technique to sports medicine and sports performance analysis and study its impact.

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