

Module 3. Kinematics introduction

Sam Baida, Chris Richter

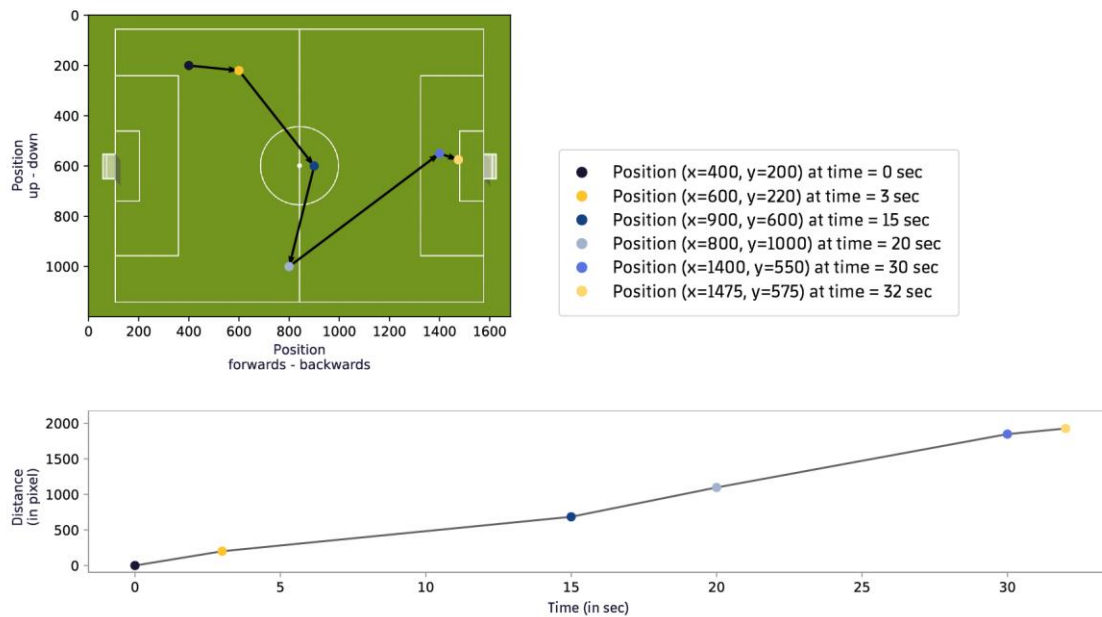
Introduction

The field of biomechanics studies the structure, function, and motion of biological systems using mechanical principles. In this module, you will be introduced to a subfield of biomechanics: human motion analysis (motion analysis), which utilizes the mechanical principles to describe the kinematic and kinetic properties of a segment/joint to describe a movement of an individual. Kinematic measures are commonly linear or angular displacements. Kinetic measures are commonly the joint moment, joint force, ground reaction force or whole-body work done.

Knowledge that can be gained from performing motion analysis can contribute to performance analysis and to the design of and evaluation of response to training programs to enhance performance, reduce injury risk or rehabilitation. You have probably been using/experiencing a kind of motion analysis system recently—while watching your favourite soccer team play, you would have been told the distance a player ran or how fast the best sprint or goal shot was. However, motion analysis systems can give more in-depth insights into sporting activities, and the information given by these systems can highlight movement deficiencies of an athlete.

Knowing an athlete's deficiencies and addressing these deficiencies using a training program can both reduce the risk of injury and improve the athlete's performance. The most commonly known and often used motion analysis systems use GPS devices to capture an athlete's position in space at different time points. These systems record the position of a sensor, which is worn by an athlete, in the real world (in respect to longitude and latitude) and a corresponding time point and are thought to present the athlete, or the whole body of the athlete (figure 1).

Figure 1: Illustrates how whole-body movements can be tracked using a coordinate system



Source: prepared by the author.

Note: The graph on the top illustrates a soccer pitch and the position of an athlete at a given time point. The graph on the bottom illustrates the distance the athlete has been moving based on the corresponding position readings.

While GPS systems can describe the movement of an athlete on a full body level (distance, speed, and acceleration), they cannot give an insight into kinematic (for example, joint angles) and kinetic measures. These measures can highlight movement differences between fast and slow runners, or if a runner carries an injurious movement pattern that can be altered during a training program. To capture kinematic and kinetic measures, we need to capture/look at movements in much greater detail and start recording joint-level kinematic and kinetic measures. By examining joint and segment kinematics and kinetics, we can get a much deeper understanding of an athlete's movement patterns and potential positive or negative characteristics. When doing a joint-level analysis, the computation of kinetic measures requires a movement analysis system that contains a force plate to measure ground reaction (Raper et al., 2014) forces. When calculating kinetic measures, the information from the kinematics and ground reaction force measures are fused and the forces on the floor allow the computation for a joint higher up the chain (the ground reaction forces allow the computation of the net forces of the ankle joint, the resulting ankle joint net-forces allow the computation of the knee joint and so on).

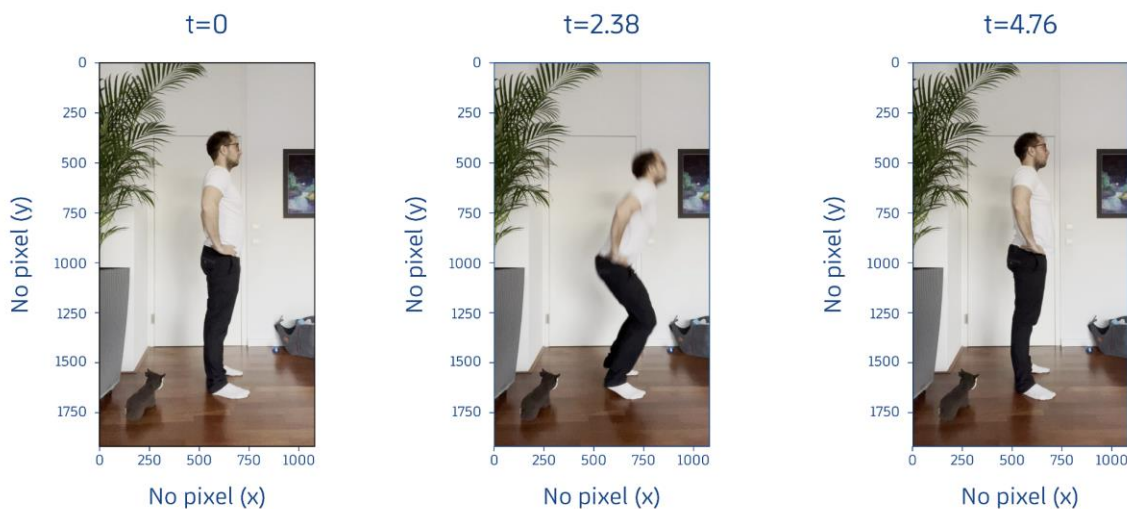
3.1 Basic Principle of Movement Capture

Capturing Kinematics

The Landing Error Scoring System (LESS) is an inexpensive clinical tool that is often used to judge jump-landing biomechanics by viewing an athlete performing a drop jump. This tool uses 17 questions to identify 'at-risk' individuals to determine an appropriate training program or to guide return to sport decisions after an anterior cruciate ligament reconstruction (Padua et al., 2009). However, the LESS score is based on a subjective scoring of a movement's key characteristic, to get objective feedback on an individual's movement you will need a system that captures a movement and enables its characteristics to be quantified.

Movement capture can be done by anyone, you just require pictures of an athlete who is positioned parallel to the camera. These three pictures taken during a countermovement jump can work as an example (see figure 2.1).

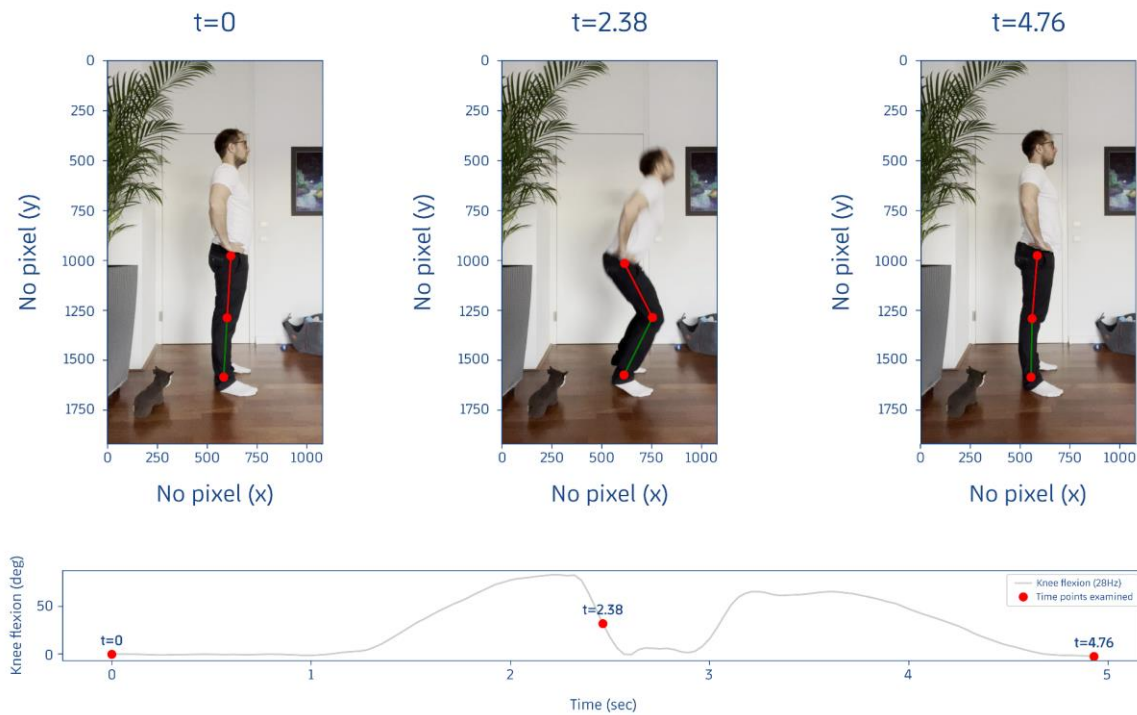
Figure 2. 1: Illustrates three images from a video recording of a countermovement jump.



Source: prepared by the author.

Note: The first image on the left is taken from the start of the movement (t=0). The image in the middle is taken from the middle (t=2.38) of the movement and the image on the right is taken at the end (t=4.76) of the movement.

Figure 2.2: Illustrates the same selection of annotated images displayed in figure 2.1



Source: prepared by the author.

Note: The dots that have been inserted into the images represent the joint centre of the hip, knee and ankle. The red line represents the femur, while the green line represents the tibia. In the bottom graph, the red displays the knee flexion angle that can be computed from the bone segments of the three images, while the grey shaded line represents information about the knee flexion magnitude that could have been computed if all images of the video would have been considered.

To describe the knee angle during the movement, we need to identify three markers: the greater trochanter, knee joint and ankle joint in each of the 3 pictures and record the x and y position of the identified marker. When you have done this, you can calculate the angle between the line that ensembles the thigh and shank using equation 1:

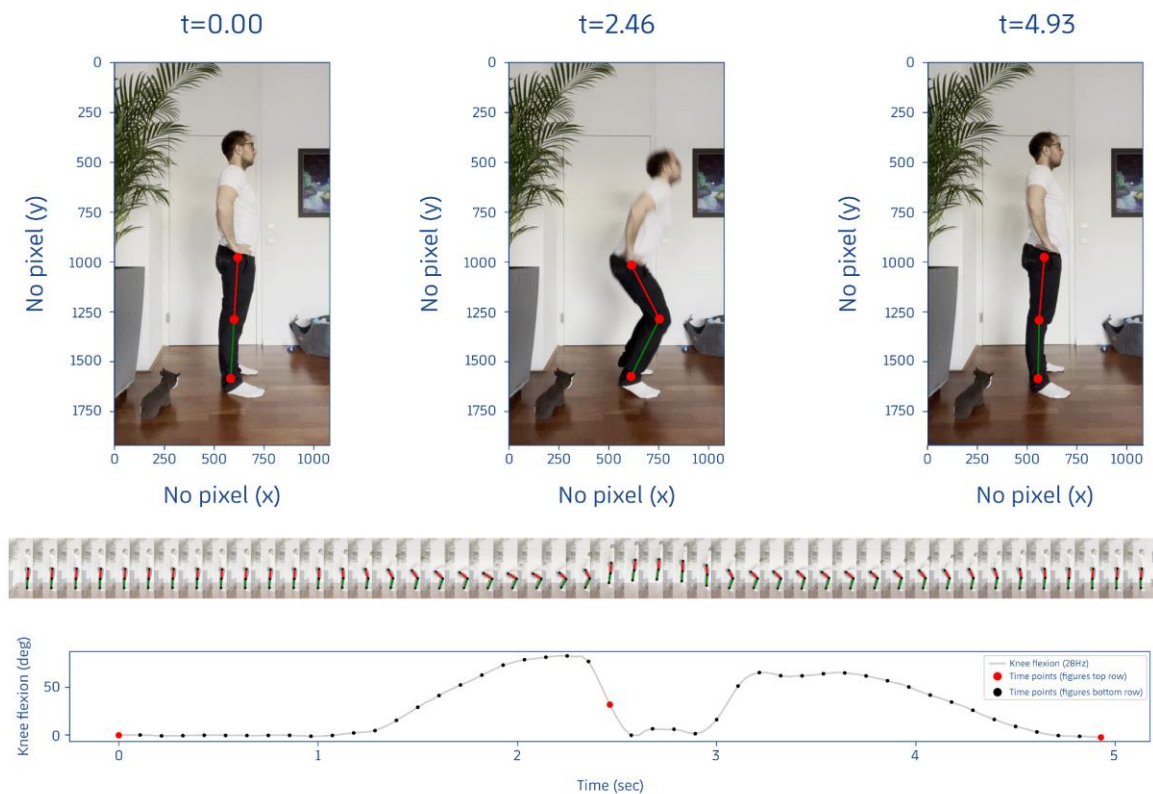
$$\tan \vartheta = \left| \frac{m_2 - m_1}{1 + m_2 m_1} \right|$$

where m_1 is the slope of the thigh and m_2 is the slope of the shank (see figure 2). The variable m is defined by the slope of both segments (equation 2).

$$m = \frac{\text{rise}}{\text{run}} = \frac{y_2 - y_1}{x_2 - x_1}$$

When examining these 3 pictures of the movement, we can see that we have successfully measured the knee joint angle of the athlete at three different time points (figure 2.2). However, it is highly likely that we have missed relevant temporal/characteristic properties of knee angle. In this example, we have missed: knee angle at the start of the movement, the peak knee angle, knee angle at the take-off and knee angle at impact on landing. To capture all these key points, we must increase the number of pictures that we obtain and examine within a given time. This is referred to as increasing the capturing frequency, a particularly important aspect of all motion analysis (as it is in force plate assessment—course “Force Assessment and an Introduction to Kinematics”). If we repeat the process using 100 pictures within the same time frame as the previous figures, repeat the process of locating the greater trochanter, knee, and ankle joint in every picture, store the x, y position of the marker and then compute the corresponding joint angle, we will have generated a much more detailed description of the knee joint angle during the jump (figure 2.3). Due to the increased capturing frequency which helped record more information, we can describe the movement and the knee angle characteristics in greater detail (in other words, maximal value and value at start, take-off, and impact). This provides an important lesson of motion analysis: a possible source of error in motion analysis is an inadequate sampling frequency (relative to the speed of the movement being assessed) which may result in important characteristics of that movement being missed.

Figure 2.3: Illustration is a build up from figure 2.2.

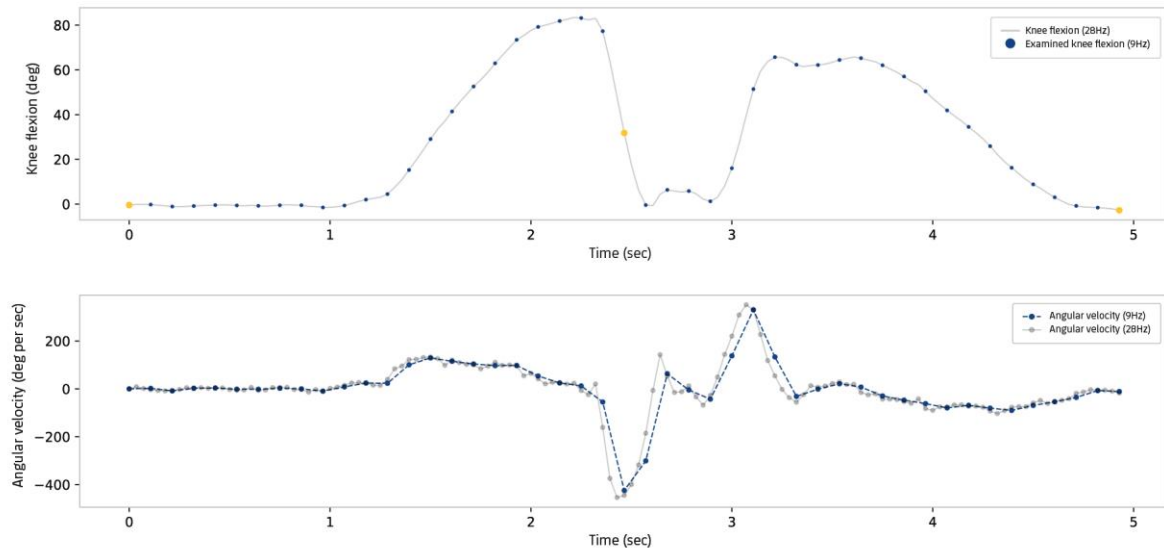


Source: prepared by the author.

Note: This illustration is a build up from figure 2.2 displays also further images extracted from the video recording (at a 9 Hz frequency; an image every .111 sec) in the middle row. The knee flexion angles that were harvested from these additional pictures are displayed as the black dots in the bottom graph.

Another possible source of error is related to marker locations. It is often the case that a marker has been placed at a location that does not exactly correspond to the anatomical landmark we were aiming to identify. This introduces a random error related to the precise location of the marker and therefore the point of interest in all 100 pictures. As we have set locations manually, we have introduced noise (in this case, a human error) into the knee joint angle, which might not be clearly visible in the knee joint angle, but it is evident in the knee angular velocity data (figure 2.4). This noise can and should be removed by utilizing one of the many data filtering/data smoothing methods available, the most common of which are the digital and spline techniques. The interested reader is referred to (Richards, 2008) for a detailed explanation of these methodologies—and their advantages and disadvantages. This teaches us another important lesson about motion analysis: a possible source of error in motion analysis is the noise introduced to the measurement by the motion analysis system used.

Figure 2.4: The top row of this figure displays the knee flexion angles as displayed in figure 2.3, while the bottom row illustrates the corresponding knee flexion angular velocity.



Source: prepared by the author.

Note: It can be seen that the angular velocity computed from unfiltered knee flexion angles contains noise that should be removed using the digital filter.

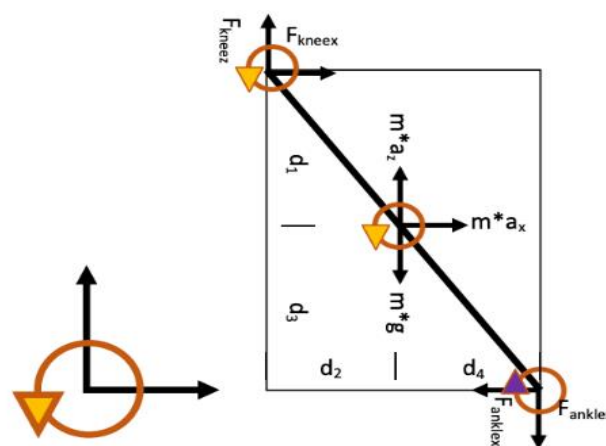
While it may seem that we have completed an accurate motion capture of the knee joint angle during the countermovement task above, we have so far not considered several factors that render the calculated knee angle inaccurate. Firstly, when computing the knee joint angles using the x and y coordinates of the identified ankle, knee and hip joint, the distance

of the pixels is not equivalent to the dimensions of the captured environment and the x and y domains must be scaled to the captured environment by calibrating the distances in our pictures. To achieve this, we can use the length of the door l that is visible in all the figures above (figures 2.1 to 2.4). This calibration reference is exactly 100 cm long, and we can therefore scale the units in the figures to real-world units if the calibration reference or the subject is orthogonal to the camera and the camera is vertical to the ground in the images. If one or other of these conditions is not satisfied, the calibration reference will not truly represent 100 cm, thereby introducing an error to our measurements. This provides us with another important lesson of motion analysis: System calibration is critical to the accuracy of our measures, and changes to calibration settings will lead to an error.

Calculation of Kinetics

To get an even deeper insight into this movement, we can also calculate kinetic measures—involving integration with force platforms. To calculate knee kinetics, we would need to also identify the heel and toe within the example, and we would need to have a force placed orthogonally and fully visible within the taken pictures. The process of computing kinetic measures is called inverse dynamics, and this section will give a brief overview on how inverse dynamics are calculated using a free body diagram for generic body segments (Winter, 2009). For the calculation of net knee joint reaction forces and moments, the kinematic description of the next distal (shank) segment and the forces from the next distal (ankle) joint is needed (for the calculation of the ankle joint kinetics, it is the foot segment, and the ground reaction forces).

Figure 3: Free shank segment diagram of the four-segment body model.



Anterior-posterior (horizontal) knee joint reaction forces are calculated as follows:

$$\Sigma F_x = m * a_x$$

$$F_{kneex} - F_{anklex} = m * a_x$$

$$F_{kneex} = m * a_x + F_{anklex}$$

Proximal-distal (vertical) knee joint reaction forces are calculated as follows:

$$\Sigma F_z = m * a_z$$

$$F_{kneez} - mg - F_{anklez} = m * a_z$$

$$F_{kneez} = m * a_z + mg + F_{anklez}$$

Where F_{kneex} and F_{kneez} are knee joint (proximal) reaction forces in the x or z direction. F_{anklex} and F_{anklez} are ankle joint (distal) reaction forces in the x or z direction. The acceleration of the CoM shank segment in the x and z direction is described by a_x and a_z , while m and g are the mass of the segment and gravity, respectively. Joint moments were calculated as follows:

$$\Sigma \text{Moment} = - (I * a)$$

$$- F_{kneex} d1 - F_{anklex} d2 + M_{knee} - F_{anklex} d3 - F_{anklez} d4 - M_{ankle} = (I * a)$$

$$M_{knee} = F_{kneex} d1 + F_{kneez} d2 + F_{anklex} d3 + F_{anklez} d4 + M_{ankle} + (I * a)$$

where M_{knee} is the joint moment at the proximal end, M_{ankle} is the joint moment at the distal end, I is the moment of inertia and α is the segment angular acceleration

3.2 Motion Capture Systems

As we described, a movement analysis can be done using a single camera. However, such a system can only describe a movement in one plane and requires the athlete to be orthogonal or parallel to the camera. To be able to record movements in more planes and to do so independently of an athlete's orientation, more sophisticated optical motion capture systems, which use the information from more than 1 camera, are required. Moreover, most commonly used systems use reflective or LED markers that can be detected automatically by the system, avoiding the need for, and potential human error associated with, manual identification of markers.

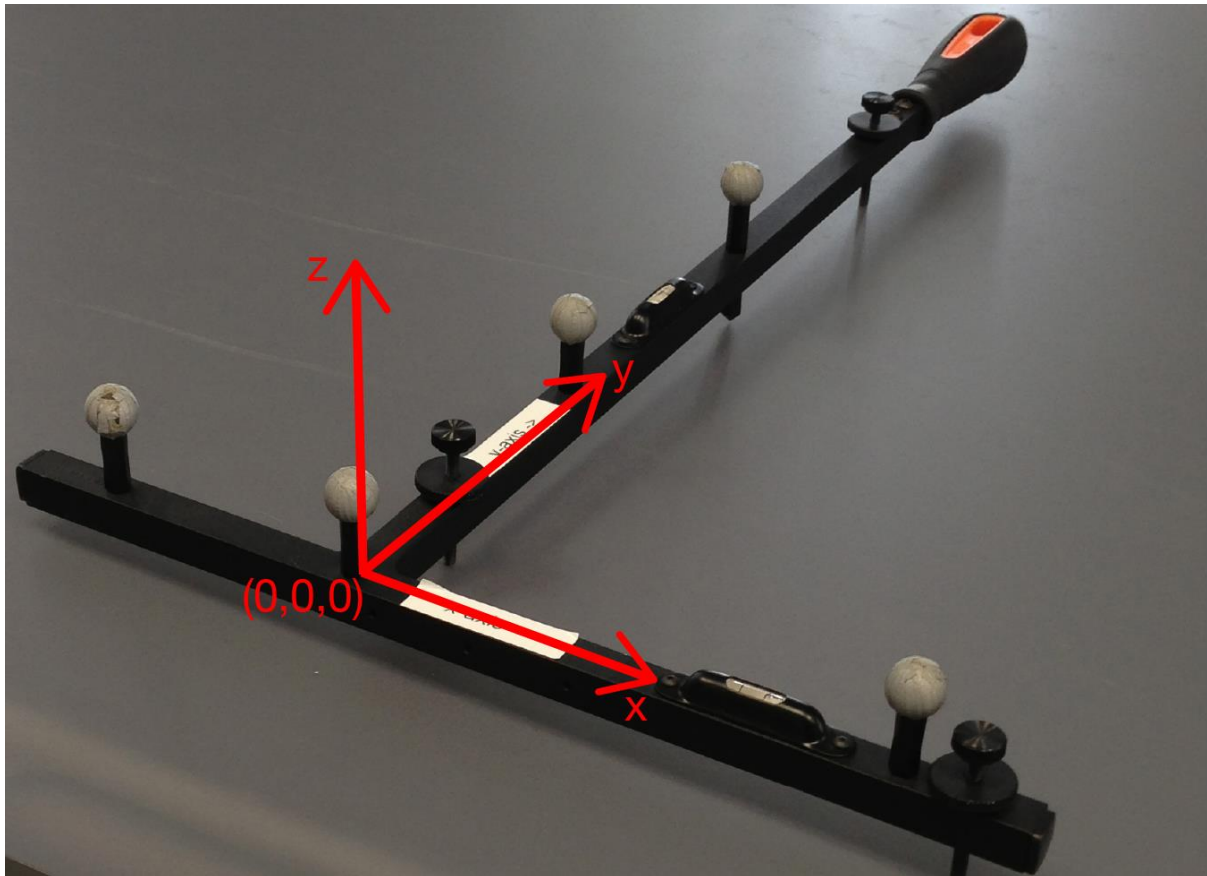
Marker-Based Optical Motion Capture

As highlighted above, motion capture relies on the description of key points captured by a camera, and one camera motion capture able to describe motion in only one plane limits our ability to fully describe a movement. To solve this, sophisticated optical systems use several cameras to track key landmarks, enabling the description of a key point in 3D and consequently the description of a movement in all three planes of motion. Additionally, to reduce the time-consuming task of manual key point identification, more advanced systems use track markers that are attached to the tracked object. To use a marker-based optical motion capture, you need to know how to calibrate the system, how to attach the markers to an individual, how to prepare and process the captured marker data as well as the resulting kinematic and kinetic data. In general, you should have a good understanding of trigonometry, calculus, and basic knowledge of mechanics. A full 3D marker-based optical motion capture system, the biggest suppliers of which are Vicon and Qualisys, can be purchased from 40k upwards, at the time of writing, and the price depends on the capture volume (denoting the area in which movement can be captured) required, number and quality of the cameras and how they are mounted (freestanding tripods vs. professional scaffolding). As highlighted in Course 1 module 1, some combination of financial and time cost and expertise requirement create substantial barriers to widespread systematic use of these systems in sports settings.

So, how does a 3D marker-based optical motion capture system work? A 3D marker-based optical motion capture system records images from multiple cameras, identifies reflective or light-emitting diode markers within these images and transforms the 2D marker positions (seen by the cameras of the system) into one 3D position—using trigonometry. To enable the system to transform the captured images into a 3D marker position, the systems must first be calibrated—a two-step process. The first step is to move a calibration frame (figure 4) with markers through the capturing volume for a given duration. The distances and angles between the markers on the calibration frame are known by the system and if two or more cameras can “see” all markers of the calibration frame at the same time, the position between

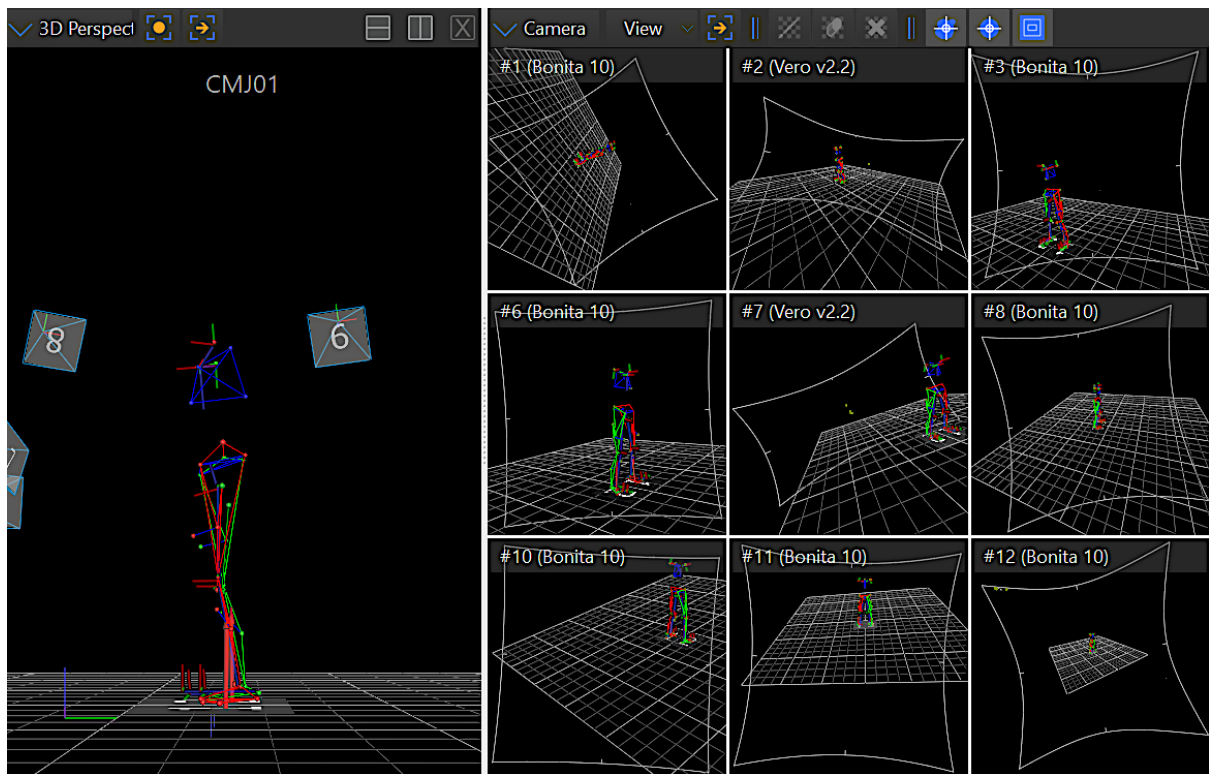
the cameras that see the calibration frame relative to each other can be calculated. This is possible because even if the marker positioning appears different in the different camera views (see example of figure 5), the actual positioning of the markers on the calibration frame is the same. The time needed for dynamic calibration is dependent on the number of cameras of the system and the number of times each camera has seen the calibration frame (set by the user) but it typically takes 1 to 2 minutes.

Figure 4: Example of a calibration frame



Source: Prepared by the author.

Figure 5: Example of calibration frame viewed from different camera positions



Source: prepared by the author

The second step is to define the origin of the coordinate system of the capturing volume, which allows the direction of the global axes the data will be described in to be set. The calibration frame is put simply on the floor, often in the middle of the measurement area of interest or where force plates are installed if being used, and the user sets the system origin. As always, the calibration step is vital, as it determines how accurate the tracked marker positions will be. Any movement or disturbance of the camera's positions after this calibration process will lead to error in the calculation of the marker positional data. Furthermore, with a marker-based optical system, the number of cameras contained within this system can influence accuracy of measurements as the more cameras see a marker the more accurately its position can be described. Also, having more cameras increases the likelihood that the markers will be continuously tracked throughout the movement – which also depends on good positioning of the cameras. Marker tracking is done on a frame-by-frame basis and if a marker (marker #1) is not “seen” by any camera for one frame, the system will treat the marker #1 as a new and different marker (marker #2) the next time it is seen. If the marker #1 is still seen by one, the system will still be able to keep the connection of the marker to the previous frame but will not be able to compute the 3D position for the marker #1 as a minimum of 2 cameras are needed to estimate the 3D position of the marker. Visual “loss” of markers will result in a significant time increase in the time cost of post-processing; missing pieces in tracking will need to be estimated and if the system automatically created a new marker you need to manually relabel marker

#2 as marker #1. As such, it is critically important to have a well set-up system before any data capture to minimize the possibility of lost connections in time to a marker and gaps in the position of a marker. The calibration of a system should take around 1-2 minutes and should be done every time you enter the lab, as you cannot be sure that cameras have not been moved. Due to the low time cost of doing so, it is recommended to recalibrate between every athlete tested. Moreover, ensure that there are no loose markers lying around the laboratory during the calibration, as those that are not on the calibration frame can also be picked up and will affect calibration.

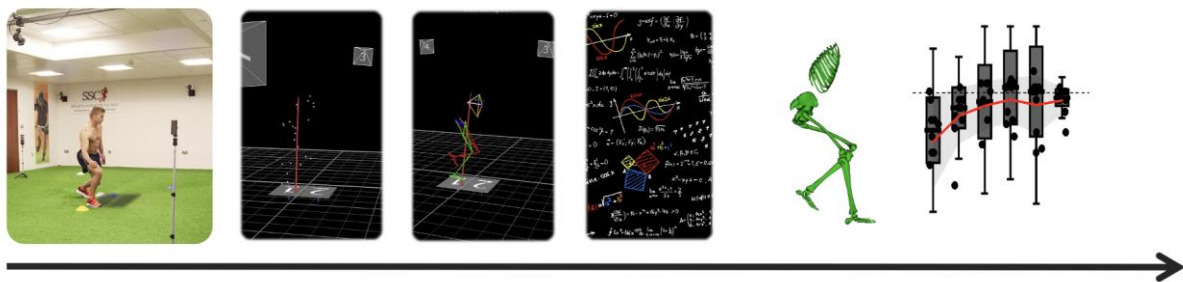
Once calibrated, we can start capturing data after the athlete has been prepared. This involves attaching the markers that are to be tracked to either anatomical landmarks or as clusters of markers on a body segment. The position of the markers to be attached depends on the marker set used and there are multiple markers sets available today (Helen Hayes, Vaughan, CAST, etc.). Each marker set was developed for a specific use; with significant variations between these models, especially evident in the different foot models available, some of which describe the foot as one rigid segment using three markers, and others, the Oxford foot model, represents the joints within the foot with 13 markers. Generally, the more markers placed on the body the more detail of the movement and potentially the greater insights can be obtained, but this also results in greater complexity and time spent preparing the athlete and processing the data—hence a trade-off between accuracy and detail on the one hand and on the other usability and frequency volume of testing that can be achieved. The marker set is later used to “drive” a skeleton/biomechanical model (inverse kinematics), whose bone orientation is then used to compute joint angles. Again, there are multiple biomechanical models. In some cases, cadaver studies are used to estimate the ankle, knee, or hip joint origin based on the attached marker, while others use movements during a “biomechanical model” calibration trial. Further, some biomechanical models use a 6 degree of freedom knee joint (motion in the joint can occur in 3 rotations [flexion and extension, external and internal rotation, varus and valgus angulation] and 3 translations [anterior and posterior glide, medial and lateral shift, compression and distraction]) while others use a 1 degree of freedom knee joint (motions in the joint can occur in only 1 rotational axis [for example, flexion and extension]).

Once the marker set and biomechanical model are chosen, and the corresponding marker set is attached, the system is set up and calibrated, so the data capture can begin. Following this, a static trial is recorded. During the static trial, the athlete stands still for a few seconds, and the chosen biomechanical model is fitted and adjusted to the markers attached to the athlete and an athlete-specific biomechanical model is stored for inverse kinematic computations. Note that functional calibration has recently been introduced to the field (Ehrig & Heller, 2019). This process involves performing a range of motion trials for every joint, which are used to identify the mathematical centre of rotation of a joint centre to which the biomechanical model is adjusted. After calibration, dynamic trials can now be recorded and, theoretically, any kind of movement can be captured. After the movement or series of

movements have been recorded, the markers can be removed from the athlete and data processing begins.

Data processing begins with the labelling of the markers, which involves telling the system which marker represents a specific position on the body of the athlete. Depending on the system and the data quality, this is done automatically or manually. The better the system is set up (number of cameras and view of cameras regarding the marker) the less time-consuming this step is. The optimal system set up is determined by an interplay between the complexity of the movements captured and the number of cameras. More complex movements require more cameras, and the capture volume in sight should be covered by > 1 camera. However, if the system is not well set up (markers often out of sight) resulting and the tracking of the markers has many missing phases, this step can become very time intensive—such that a few seconds can take hours to process.

Figure 6: Data processing



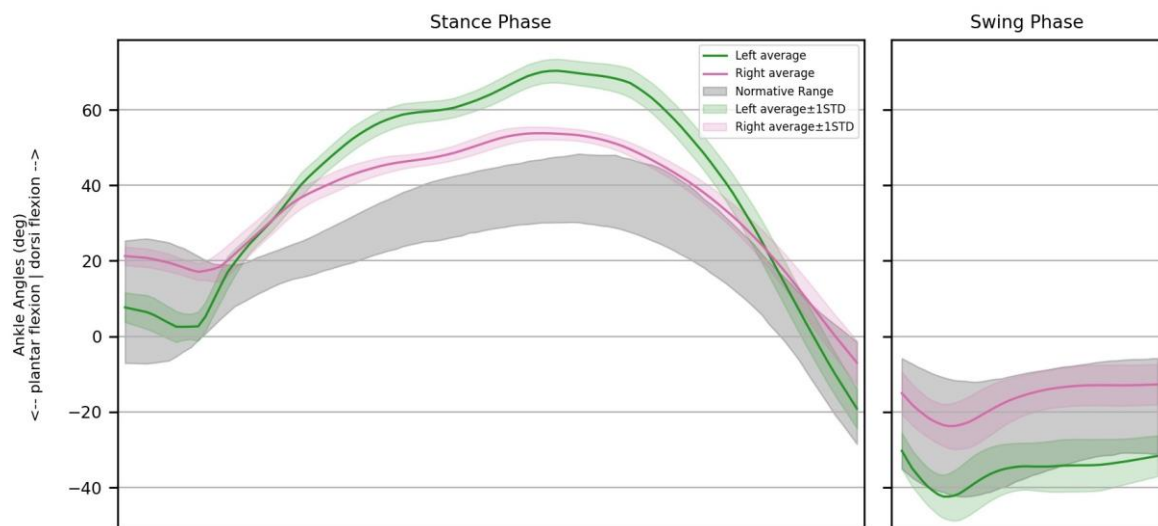
Source: Prepared by the author

Once the markers are labelled, gaps in marker tracking need to be filled in. This is commonly done manually, but can also be done with “set up pipelines”. Pipelines are algorithms that can be set within the analysis software to automate the selection of the options listed below for gap filling.

During the gaps filling steps, the process is to estimate the marker position of phases where a marker has been covered. This is done using three main principles: segment fill, pattern fill, spline fill. Of these, the segment fill approach is the most accurate. To apply the segment fill option, a minimum of 3 other markers of the segment needs to be on the segments and visible. If this is the case, you can use the relationship of the distances of the markers on the segments to calculate the theoretical position of the missing marker and as the distances between the markers of the segment should change only marginally (due to skin movement) this is the best way to fill a gap. However, there are occasions when there are either less than 3 other markers on the segment or less than 3 markers visible. In these cases, the trajectory of another marker that behaves and moves similarly to the missing marker can be used to fill in the covered phase—for example, using a marker close by on the same segment or one which highly correlates with the marker with the data gap. This involves copying the movement trajectory of the marker with the similar movement pattern onto the missing marker. The last

option is a spline fill, a process which should be done only if no other information about the trajectory of the marker is available. The spline fill uses the signal of the marker it is lost from vision and immediately after it reappears and estimates the behaviour of the signal during the period when it was lost using a mathematical polymeric filling process. This is considered the least accurate option and should only be used as a last resort. Once labelling is done, the data needs to be filtered to remove any system noise and the last step in the process is referred to as the modelling step. During the modelling step, the previously generated athlete-specific-biomechanical model is fitted into the dynamic trial on a frame-by-frame basis, based on the position of the recorded markers. You could say it is set into motion. The position or orientation of the bones of the set-in motion biomechanical model are then used to compute joint angles (inverse kinematics). Most models use positive and negative magnitudes to imply flexion and extension of a joint. This can differ between models, and it is advised to plot the direction of a joint into illustrations to ensure this is clear and represents what you think it does.

Figure 7: Multiple force plate kinematic display.



Source: Prepared by the author

If the motion capture system that is used also contains one or more force plates, the combination of the kinematic information and the ground reaction forces can be used to compute net joint moments and force using inverse kinetics. A possible error that can be introduced to kinetics measures, apart from the potential sources or errors mentioned for kinematic measures, relate to poorly set up force plates (not level with the floor, or do not have full contact to get ground on its contact points) or in a movement assessment the athlete has both limbs in contact with one platform.

Marker-based optical motion capture systems are considered the gold standard of motion capture because of their accuracy in marker tracking (less than 0.5-mm error) when set up correctly (Merriau et al., 2017). However, the kinematic and kinetic measures are computed from a biomechanical model that is driven by the markers. Hence, the misplacement of

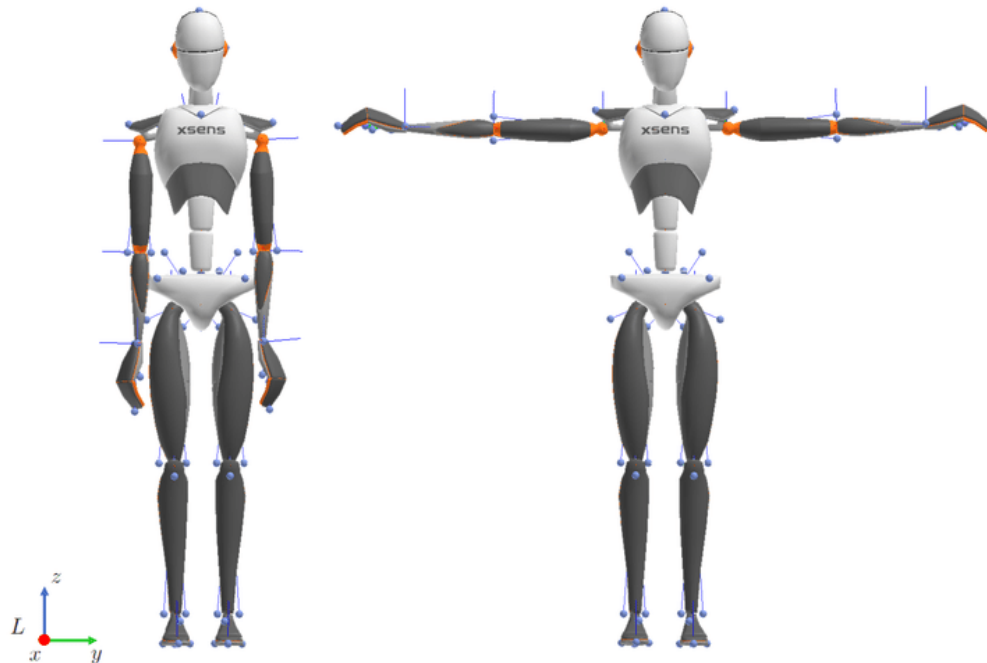
markers (not placed accurately on the specified landmark), soft tissue movement (that shift the markers from their original position), poor gap filling and changes in intensity of sunlight, or movement of cameras post calibration, are all factors that can undermine the accuracy of the calculated output data of interest. Furthermore, the biomechanical model chosen to generate the kinematic and kinetic measures has a huge impact on these outputs and therefore the interpretation of the movement. The same data fed into different biomechanical models can generate very different outcomes. For example, Richter et al. (2020) reported that sagittal angles (for example, knee flexion or hip flexion) were highly reliable when using the same data analysed using different biomechanical models, while angles in other planes of movement (knee abduction) were not. However, the biggest disadvantage of marker-based optical motion captures is that they are restricted to the capturing volume (area) made available by the fixed cameras and large capturing volumes are complicated and expensive—for example, capturing a 100 sprint or a marathon. Additionally, attaching markers to be captured can take up to 45 min (depending on the marker set and the attachment accuracy).

Sensor-Based Motion Capture

The motion capture systems that can record movements across large capturing volumes are sensor-based motion capture systems, for example, those that utilize inertia measurement units (IMU). IMU sensors, which combine accelerometer, gyroscope and magnetometer, can estimate changes in position and orientation by integrating these measurements. The integration of accelerations from the accelerometer can estimate the position of a sensor or the change of position in time. The integration of angular rotation from the gyroscope to the estimated orientation of a sensor and the change of orientation. The magnetometer is needed to determine the orientation of a sensor using the earth's magnetic field. When using IMUs the process during data capture is somewhat like the process for the marker-based optical motion capture systems, without the need to calibrate the capturing volume (which is not a time-consuming process).

As with the marker-based optical motion capture systems, IMU sensors need to be attached to anatomical landmarks on the human body, and generally do so with Velcro straps, double-sided tapes or other. As is the case with the marker-based optical movement analysis systems, the positions of the IMU sensors are determined by the biomechanics model that is going to be driven by the sensors. The next step in an IMU data capture is the static calibration. This is again similar to the static calibration in the marker-based optical movement analysis systems, and the athlete has to stand still in an N-Pose or T-Pose.

Figure 8: Illustration of N-pose (left) and T-pose (right).



Source: Xsens.com

After the static calibration, the reading recorded by the IMU sensors are either stored on the device or it is sent to a computer via a wireless connection or both. With an onboard storage system, the user needs to upload the data after the test capture for processing, while systems that send data directly to the computer can view the sensor readings in real time, which can drive the biomechanical model producing a real-time avatar animation. In case of connection loss of the sensor to the computer, most sensor systems save “lost” data onboard that can be downloaded afterward when connection is re-established. When using an IMU system, it is recommended that the data is streamed to a PC and that the driven biomechanical model can be visually checked for its correctness. Because if, for example, an IMU sensor moves during the data capture, any subsequent measures are erroneous, and you could redo the data capture. A difference with the marker-based motion capture system is that sensor-based systems do not need labelling or gap filling as the IMU sensor is placed on a specific position because all data should have been transmitted or can be downloaded from the onboard storage. As with the marker-based optical motion capture systems, the correctness of kinematic measures recorded by an IMU system are dependent on IMU sensor placement. Further, in IMU systems, marker movement might cause errors (for example, the IMU sensor moves after performing several trials or during a run). Further, the fundamental concept upon which IMU’s are based—integrating signals can generate an error in kinematic measurements because small errors (in measurement accuracy) accumulate over time. This phenomenon is

known as **drift** and can be caused by environmental factors (such as heat, humidity and so on). To counter the drift of an IMU sensor, IMUs system providers use Kalman filters or gradient descent optimization algorithms to remove the effect of sensor drift (noise) by fusing the sensor data (drift is independent across sensors).

An advantage of an IMU motion capture system over optical motion capture is that there is no capture volume restriction, and that IMU sensors can capture data even if they are occluded (like during a rugby tackle). However, the kinematic measures are also computed from a biomechanical model that is driven by the IMU sensors and therefore the same issues generated by misplacement of sensors also apply (for example, if the sensor is not placed on the requested landmark). Soft tissue movement and other sensor movement (that offset the markers from the intended position) will impact the resulting kinematic measures. Further, the biomechanical model used to generate the kinematic measures also has a considerable impact on the data and the same data fed into different biomechanical models can generate different outcomes.

Regarding kinetic measures and IMU-based systems, unlike in optical systems, it is difficult to synchronize the position data given by the force plate(s) and the IMU system. Hence, the calculation of joint moments is erroneous (small changes in centre of pressure to the application on the foot have large impacts). To overcome this, additional software can be used, which generates **estimations** of ground reaction force which are subsequently then used to compute kinetic measures via muscular simulations (see AnyBody software: <https://www.anybodytech.com/>).

The best providers of IMU systems at the time of writing are XSens and Noraxon

Marker-Less Optical Motion Capture

The last motion capture option discussed here are the marker-less optical systems. These systems function similarly as the marker-based optical systems but without the need to place markers on the athlete, overcoming two of the major disadvantages of the marker-based optical and sensor motion capture systems—the time cost of marker/sensor placement and the potential for marker/sensor misplacement. Instead, these systems use computer vision techniques to estimate the position of key landmarks that drive a biomechanical model. To generate a marker-less optical motion capture system, a machine learning algorithm needs to be trained so that it enables the identification of the key points needed by the biomechanical model. The quality and error of these estimations is related to the “ground truth” data used to train such a model. For example, a model could be trained on data that contains manually labelled figures (key points were identified by a human like we did above) or on data which had an X-ray and camera synchronized to identify key points and in each case the quality of the outcome data generated with each method would be very different. However, as the machine learning algorithm is validated using the existing defined “ground

truth” data both approaches could market their system as “highly” accurate, while only the X-ray option would really have learned the position of key points of the biomechanical model as the human labelling option carries human estimations. Another option to capture a movement using marker-less techniques is via background subtraction. Background subtraction refers to a process that identifies objects that are in the front of a figure and generates a silhouette of the object. With the use of multiple cameras views the identified silhouette can be used to estimate the shape, to which a biomechanical model can be fitted.

The advantage of marker-less systems over others is that there is no need to attach markers or sensors to the athlete; however, as with marker-based systems, they are limited to a capture volume. The major disadvantage of these systems is that they are still in their infancy in terms of development iterations and are considered to be the least accurate of the presented systems. However, they are very likely to improve in the coming years.

The most advanced provider of marker-less optical motion analysis systems at the time of writing is Theia marker-less.

Summary

The reader should note that the performance of all the systems presented depends heavily on marker or sensor placement of key point identification. In general, the optical systems are more accurate than IMU sensor-based systems, as they suffer from drift, but they have the clear benefit of not capturing volume restriction. However, other sensor-based systems might overcome this limitation such as Kinexon (<https://kinexon.com>), which uses radio frequency sensors. However, these are only a whole-body positions analysis system. Overall, the biggest impact toward the kinematic data is the chosen biomechanical model used and the issues like wobble mass that can affect the accurate, precise and reliable location of key points, regardless of the system used. Nevertheless, joint angles on a sagittal plane (ankle, knee, hip, and thorax flexion) are likely to be reliable between sensors, while other plane angles (knee abduction and rotation or ankle eversion) will be impacted largely by the biomechanical models chosen regardless of the technology used.

Processing movement data

After movement data has been captured, and pre-processed, the captured data needs to be processed. The data processing step is concerned with data hygiene and is a fundamental step ensuring only “clean” and reliable data is being used during your analysis and interpretation. There are several steps within data processing which relate to data filtering and event detection. Data filtering is performed to remove noise or unwanted information from your data that might have been introduced. Noise refers to small random errors in the data (such as digitizing errors or skin movement) that can be removed using smoothing algorithms or filters (Winter, 2009). However, as stated earlier, you should be careful when using filters because they can affect the amplitudes of measures (Mai et al., 2019) and in turn the conclusions of studies and analyses. For example, as stated by Sigurðsson et al.:

With respect to filtering strategies, marker data requires a much lower cut-off frequency than force plate data, but filtering them unevenly produces artificially large impact artifacts while filtering both signals equally removes the impact peak. The only prospective study that found a link between knee KAM [abduction moment] and ACL injury risk used an uneven filtering strategy that produces artificially large impact artifacts, and was therefore more likely to identify the KAM peak in the early stance that is consistent with the timing of injury. (2021, p. 2)

Another crucial step in motion capture data processing is event detection. This refers to the identification of, for example, the start and end of a movement cycle and other key points

(like end of eccentric phase). For example, when capturing a movement, you will collect data before the phase of interest or multiple trials. Event detection enables the captured data to be split into multiple sections—such as trials and phases, from which you can then extract your key data and performance indicators. There are various methodologies or approaches used to define and identify key events within raw or processed signals. On this note, the availability of a force plate will make events like take-off and impact (landing) easy to identify, while other events like the start of the CMJ or the end depend on the practitioner, researcher, or software provider. A possible error that could be introduced in this step is the failure to synchronize the motion capture system and the force plates. While event detection can also often be done manually in the motion capture software or using software to automatically detect events, the more complex the movements/exercise you are analysing, the less likely it is that there is software available that has automated this process. Manual identification is very labour intensive and as such, it is recommended that if a movement is not commonly used or software is not available to automatically identify relevant events, coding using programs such as MATLAB (licence is needed) or Python (open source) should be created to automate to do so.

Analysis of motion data

With the completion of data capture and data processing, the data analysis can be started. During this step, you should have a clear aim in mind (performance or injury related question about the athlete you aim to answer with the assessment) to select the most appropriate methodology.

The most commonly used approach to examine movement data is discrete point analysis. A discrete point is a measure of the characteristic of a waveform between two defined events (for example, the maximal magnitude of the knee flexion angle between the start of the eccentric phase and the end of the concentric phase of the movement cycle) or at a defined time point (like the knee flexion angle at zero centre of mass velocity). Another example of discrete point analysis is the variability of a $1 \times n$ vector that holds the magnitudes of a point during n trials. For example, if you have captured 5 jump trials, this vector would be a 1×5 (one subject and five trials). Another measure that might determine this data is variability in left-right force or impulse outputs or asymmetries—which are often of interest in performance and biomechanical analysis (Bishop et al., 2018) (also see course 1 and 2). Commonly used discrete points include performance measures (jump height or distance, ground contact time or completion time or both), and local extremes (minima or maxima; knee flexion or extension angle). Discrete points are frequently used because they allow the reduction of the complete time dependent biomechanical data to specific points within two events (for example, between impact and toe off in a drop jump or start of movement to toe off in a countermovement jump) to a single, clearly defined measure, reducing the processing time and helping us to interpret findings. However, the data reduction advantage is also a

limitation, as the selection of the set of discrete points to be examined will be based on prior knowledge (previous research or professional experience), the variables selected by the software providers based on these, or *post hoc* analysis. Consequently, while a discrete point analysis helps understand and comparing movements, there is potential:

- to discard important information which may include insightful features (Donà et al., 2009; Donoghue et al., 2008);
- to compare features that present unrelated neuromuscular capacities as a peak value might occur at different time points (for some people in eccentric phases, while for others in the concentric phase) that could lead to misleading conclusions (Richter et al., 2014);
- to encourage a search for discrete points that are different between two groups, called fishing for significance (nontrivially biased non-directed hypothesis testing), which could also lead to misleading conclusions and false positive results (a statistical term for an error that lets none differences appear different) (Pataky et al., 2013).

Another way to examine the captured data is by examining the whole movement signal between two set events (**waveform analysis**). There are a variety of statistical techniques available to examine and the most commonly used one are: statistical parametric mapping (Pataky et al., 2013), and (functional) principal component analysis (Warmenhoven et al., 2019), while many others have been used in biomechanical studies (Dixon et al., 2013). However, before such an analysis can be done, the number of measures taken within the starting and ending event need to be normalized to a chosen number so that the analysis technique can compare like with like. For example, when comparing the kinematics of different running speeds, the contact time of one condition might be only half of another and no data exist for some waveforms if the data is not time normalized. To perform a time normalization, the research needs to select several frames to normalize to—typically 101 so that every frame corresponds to a percentage within the movement cycle (0%-100%). However, this should not arbitrarily be set to 101 because this will be substantial oversampling of your data if some samples contain only 5 measures and could therefore result in a poor shape estimation of the curve, in which case you should consider increasing your sampling rate. In contrast, if you have 1000 measures, down-sampling to 101 frames might result in loss of important information. Another consideration in waveform analysis is the start of different neuromuscular characteristics of the movement (eccentric phases vs. concentric phases). When the waveform is time normalized, it is very likely that some samples in your database are still in an eccentric phase, while others are already in a concentric phase. This is referred to as phase variability and can be accounted for by a process called landmark registration, which describes a mathematical process that aligns an event within a sample of data samples such as the start of the concentric phase in such a way that it occurs in every trial at a pre-set point in time (like 37%). This is done by generating a warp function, which alters the domain time of a signal from linear to a nonlinear, thereby accounting for phase

variability between athletes in a cross-sectional comparison or in an athlete over time when monitoring. The interested reader can get more detail in references (Moudy et al., 2018).

Reading movement analysis studies

While many biomechanical studies provide data relevant to injury risk and rehabilitation, their interpretation and applicability to practice can be an issue. The biomechanical models and variability in processing across studies and variations related to the different movement capture systems used and the quality of statistical analysis can lead to different findings. Hence the practitioner should read findings with a critical eye, not only the abstract and conclusions, but also the detail of methods, processing, and statistical analysis and compare these with similar studies. Refer to a statistician or upskill in respect to statistical methods if need be. Consider the sample size of the cohort and the population—both will have a big impact on findings and the wider applicability to the sport, level, gender, age group you are working with. Another aspect of study interpretation is the decision of what variables to examine and ensuring you understand how a variable is calculated, as this can vary considerably across kinetic and kinematic studies. Furthermore, when reviewing studies that examined kinematic measures, one should consider the reported values in respect to a joint active range of movement, which will make you aware of possible limitations in the biomechanical models used throughout the study.

In summary, when reading biomechanical studies, one needs to carefully consider the limitations of the study and the generalizability of findings. Furthermore, best practice within prospective risk studies is setting aside a portion of their data which is only used for the validation of findings by running this through the generated model (e.g., regression equation to predict injury). Unfortunately, validation/evaluation is not yet commonly used in sports science studies (Richter et al., 2021).

References

- Bishop, C., Turner, A. & Read, P.** (2018). Effects of inter-limb asymmetries on physical and sports performance: a systematic review. *Journal of sports sciences*, 36(10), 1135–1144. <https://doi.org/10.1080/02640414.2017.1361894>
- Dixon, P. C., Stebbins, J., Theologis, T., & Zavatsky, A. B.** (2013). Spatio-temporal parameters and lower-limb kinematics of turning gait in typically developing children. *Gait & posture*, 38(4), 870–875. <https://doi.org/10.1016/j.gaitpost.2013.04.010>
- Donà, G., Preatoni, E., Cobelli, C., Rodano, R. & Harrison, A. J.** (2009). Application of functional principal component analysis in race walking: an emerging methodology. *Sports biomechanics*, 8(4), 284–301. <https://doi.org/10.1080/14763140903414425>
- Donoghue, O. A., Harrison, A. J., Coffey, N., & Hayes, K.** (2008). Functional data analysis of running kinematics in chronic Achilles tendon injury. *Medicine and science in sports and exercise*, 40(7), 1323–1335. <https://doi.org/10.1249/MSS.0b013e31816c4807>
- Ehrig, R. M. & Heller, M. O.** (2019). On intrinsic equivalences of the finite helical axis, the instantaneous helical axis, and the SARA approach. A mathematical perspective. *Journal of biomechanics*, 84, 4–10. <https://doi.org/10.1016/j.jbiomech.2018.12.034>
- Mai, P., Mählich, D., Fohrmann, D., Kurz, M., Trudeau, M., Hamill, J., Weir, G. & Willwacher, S.** (2019). Cut-off frequencies matter: the effects of filtering strategies and footwear on internal knee abduction moments in running. *Footwear Science* 11(1), 44-46. <http://dx.doi.org/10.1080/19424280.2019.1606069>
- Merriault, P., Dupuis, Y., Bouteau, R., Vasseur, P. & Savatier, X.** (2017). A study of vicon system positioning performance. *Sensors*, 17(7), 1-18. <https://doi.org/10.3390/s17071591>
- Moudy, S., Richter, C., & Strike, S.** (2018). Landmark registering waveform data improves the ability to predict performance measures. *Journal of biomechanics*, 78, 109–117. <https://doi.org/10.1016/j.jbiomech.2018.07.027>
- Padua, D. A., Marshall, S. W., Boling, M. C., Thigpen, C. A., Garrett, W. E., Jr, & Beutler, A. I.** (2009). The Landing Error Scoring System (LESS) Is a valid and reliable clinical assessment tool of jump-landing biomechanics: The JUMP-ACL study. *The American journal of sports medicine*, 37(10), 1996–2002. <https://doi.org/10.1177/0363546509343200>
- Pataký, T. C., Robinson, M. A., & Vanrenterghem, J.** (2013). Vector field statistical analysis of kinematic and force trajectories. *Journal of biomechanics*, 46(14), 2394–2401. <https://doi.org/10.1016/j.jbiomech.2013.07.031>
- Richards, J.** (2008). *Biomechanics in clinic and research: an interactive teaching and learning course*. Churchill Livingstone.

Richter, C., Daniels, K. A. J., King, E. & Franklyn-Miller, A. (2020). Agreement between Inertia and Optical Based Motion Capture during the VU-Return-to-Play- Field-Test. *Sensors* 20(3), 1-18. <https://doi.org/10.3390/s20030831>

Richter, C., O'Connor, N. E., Marshall, B. & Moran, K. (2014). Comparison of discrete-point vs. dimensionality-reduction techniques for describing performance-related aspects of maximal vertical jumping. *Journal of biomechanics*, 47(12), 3012–3017. <https://doi.org/10.1016/j.jbiomech.2014.07.001>

Richter, C., O'Reilly, M., & Delahunt, E. (2021). Machine learning in sports science: challenges and opportunities. *Sports biomechanics*, 1–7. <https://doi.org/10.1080/14763141.2021.1910334>

Sigurðsson, H. B., Karlsson, J., Snyder-Mackler, L. & Briem, K. (2021). Kinematics observed during ACL injury are associated with large early peak knee abduction moments during a change of direction task in healthy adolescents. *Journal of Orthopaedic Research* 39(10), 2281-2290. <https://dx.doi.org/10.1002%2Fjor.24942>

Warmenhoven, J., Cobley, S., Draper, C., Harrison, A., Bargary, N., & Smith, R. (2019). Considerations for the use of functional principal components analysis in sports biomechanics: examples from on-water rowing. *Sports biomechanics*, 18(3), 317–341. <https://doi.org/10.1080/14763141.2017.1392594>

Winter, D. A. (2009). *Biomechanics and motor control of human movement* (4th ed.). John Wiley & Sons.