Automatic 2D Motion Capture System for Joint Angle Measurement

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Abstract. Joints angles are some of the most common measurements for the evaluation of lower limb injury risk, specially of lower limb joints. The 2D projections of these angles, as the Frontal Plane Projection Angle (FPPA), are widely used as an estimation of the angle value. Traditional procedures to measure 2D angles imply huge time investments, primarily when evaluating multiple subjects. This work presents a novel 2D video analysis system directed to capture the joint angles in a cost-and-time-effective way. It employs Kinect V2 depth sensor to track retro-reflective markers attached to the patient's joints to provide an automatic estimation of the desired angles. The information registered by the sensor is processed and managed by a computer application that expedites the analysis of the results. The reliability of the system has been studied against traditional procedures obtaining excellent results. This system is aimed to be the starting point of an autonomous injury prediction system based on machine learning techniques.

Keywords: Motion capture · 2D analysis · Frontal Plane Projection Angle · Reflective markers · Kinect

1 Introduction

Lower limb injuries are the most common injuries among sport practitioners [1,2]. In particular, injuries in the knee joint complex are very feared due to their complexity and the expensive, long and painful rehabilitation periods involved [3,4]. In the light of that, it appears the opportunity to develop new technologies to support experts during the rehabilitation task of knee injuries, reducing the impact of the process over the wounded subject.

One of the most commonly used measurement to evaluate the knee physical state is its alignment angle, usually known as knee valgus or varus. It gives us information about the knee-complex strength: a low angle value means high knee strength. A quantitative measurement of this angle was introduced by Wilson et al. [5] in 2006, the Frontal Plane Projection Angle (FPPA). It consists of the projection of the knee angle over the frontal body plane (Fig. 1). Subsequent researches have shown a reliable relationship between FPPA and some knee injuries.

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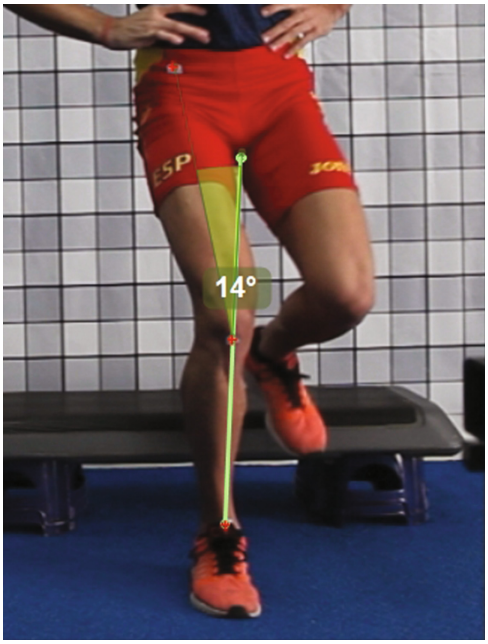

Fig. 1. Frontal Plane Projection Angle (FPPA)

Current FPPA measurement methods involve the offline analysis of previously recorded video frames, placing markers and lines by hand. This process introduces human-made errors due to wrong marker placement. Moreover, the user needs to find exactly the frame with the higher FPPA value, which implies measuring the angle on almost any video frame. In the light of these limitations, this work presents a novel automatic video analysis system intended to support experts in the dynamic measurement of 2D biomechanics angles, including FPPA in a cost-and-time-effective way. The system makes use of an infrared camera to track retro-reflective markers attached to the subject's joints. The measurement of the angles is computed from the marker's coordinates. A computer application with an intuitive user interface has been implemented to support and simplify expert's routine and expedite the analysis of the results.

This system is aimed to be the starting point of a complete injury prediction system that, autonomously, gives experts indications of subject's injury risk and performance status. Some approaches of injury prediction can be found in the literature. In [6], multiple computational intelligence methods such as artificial neural networks and Bayesian networks are compared when performing quantitative risk assessment of injuries. Another research [7] summarizes the predictive factors of sports injuries (which include knee alignment) and proposes a mathematical prediction method based on logistic regression. Hewett et al. [8] also relate the knee valgus load during landing tasks with the anterior cruciate

ligament injury. In [9,10], wearable sensors are used to monitor physical performance status.

The paper structures as follows. In Sect. 2, the proposed system is described. The validation procedure followed and the results are shown in Sect. 3. Finally, Sect. 4 summarizes the issues addressed in the paper and presents the conclusions.

2 System Description

The proposed system is composed of three key elements. The first one is the group of retro-reflective markers used to track the exact position of the desired body joints. They are placed over the subject's body. Those markers are made of retro-reflective material in order to avoid problems with the viewpoint of the camera. Any marker shape is allowed provided that the size of the marker is not excessively big. The markers used in this project are depicted in Fig. 2a. They are spherical markers with a diameter of 6.4 mm.

(a) (b)

Fig. 2. (**a**) Spherical retro-reflective markers; (**b**) Kinect V2 sensor

The second key element is the depth sensor. This system has been designed to operate on the depth data provided by the Kinect V2 sensor (Fig. 2b). Kinect is well-known for being a markerless system, but some researches have demonstrated that Kinect's pose estimation algorithm is not accurate enough for precise clinical applications [11,12]. In order to increase the accuracy of the measurement, the aforementioned markers are placed by an expert on the exact anatomical points corresponding to the body joints. The depth sensor tracks the position of the markers and uses Kinect's algorithm to avoid tracking any reflective element in scene that is not a marker. Another purpose of the markers is to allow for tracking points that are not joints, but whose measurement is useful (e.g. the breastbone).

The last element is a computer application that processes data on-the-fly and stores them into a local database. The main feature of the application is the real-time FPPA computing, giving this value to the user with no need of offline analysis. In the following, all the application features are thoroughly described, as well as the process of the data acquisition and processing.

2.1 Data Acquisition and Processing

As it has been explained before, the marker tracking is one of the main tasks of the current work. In order to provide a precise recognition of the markers with no need of external light sources (thereby contributing to the easiness-of-use objective of the system), the depth camera of the Kinect V2 sensor is used.

The Kinect's depth sensor consists of an infrared CMOS camera and three infrared (IR) emitters. Its operation principle is the Time-of-Flight (ToF) [13,14]. It emits a modulated IR pattern which is reflected on the marker and captured by the camera, which captures the intensity of the reflected pattern for each pixel. Each data frame is composed by a 512×424 (resolution of the camera) array of 16-bit IR intensity values, one for each pixel. A greyscale image is constructed with these values and shown in the application.

As they are retro-reflective elements, the intensity value of those pixels which belong to a marker is appreciably higher than the rest of values, so it is straightforward to isolate every pixel that accomplishes this condition through a high-pass filter. Once this filtering has been done, we have an array with the index of those pixels belonging to a reflective element in scene, so the next step is to classify those pixels and determine whether they are a part of a marker or any other reflective element, and which marker they belong to. In this part we apply Kinect's pose estimation algorithm to set a neighborhood of pixels around each estimated joint (Fig. 3). The pixels inside this neighborhood belong to this joint's marker. As the markers are sufficiently far from the rest of them, there is no risk of pixel mismatch. The rejection of unwanted reflective elements is a key part of the process, since it reduces the algorithm workload and improve its robustness.

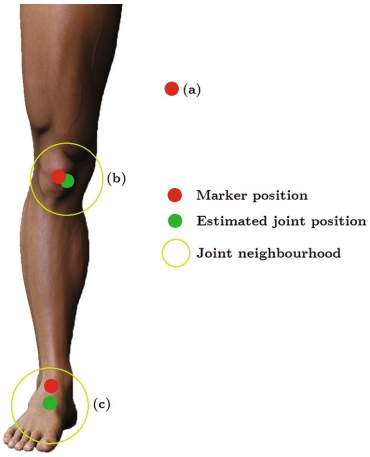

Fig. 3. Reflective pixels: (**a**) reflective element which is not part of a marker, not tracked, (**b**) knee marker pixel, (**c**) ankle marker pixel [15]

After the classification, the centroid of each group of pixels is computed, and its coordinates are considered the marker's coordinated (thus, the joint's coordinates). This consideration increases accuracy and makes the process independent of the subject's distance of the sensor, and the marker size and shape. The aforementioned process is repeated at the arrival of each data frame to perform the motion capture.

These points are used to calculate the desired joint angles. For example, for the FPPA we use the information of hip, knee and ankle position. As the angles are relative and depend only on the markers' position, the measurements are robust against accidental camera rotations. It is worth to notice that the angles are projections over the frontal body plane, so there is some information loss in relation to the 3D angle value.

2.2 Application Description and Implementation

In this section, the computer application used to manage and store the data acquired is described. The aim of this application is to speed up the expert task when performing angle measurements and analyzing those data. The storage of the data and the patients' information relies on a local SQLite database [16] deployed in the user's computer storage disk. The database file is created on the first use of the application. The SQLite database engine has been chosen because it adjusts to the characteristics of this system, since the amount of data managed is able to fit in a single disk file and there will not be concurrent queries to the database. Its good performance on the current task makes it preferable than a client/server engine. In order to provide personal information protection and data anonymity, the information has been decoupled into two data tables. One of them stores patient's personal information and the other one the data registered. Both tables are related by an unambiguous personal ID number, which is assigned to each patient when is registered into the database for the first time. The patient's data table can be modified by the user, who can add, edit or remove profiles. The data table is automatically filled and can only be read.

Once the profiles have been added to the database, the user can perform a great variety of tests to measure the lower limb joint angles, like the FPPA. At this stage one test has been implemented, the Single Leg Landing (SLL) test, which will be explained in Sect. 3. Figure 4 depicts the main screen of the SLL test, which includes the camera image, a control panel and a status bar. The image displays the infrared camera bitmap, which shows the camera image in greyscale, based on the intensity value of each pixel (see Sect. 2.1). For a better angle visualization, a see-through canvas is positioned over the image, where the markers are represented by red circles and connected by yellow lines. Those shapes are attached to the markers' coordinates, so their position is dynamically updated as the subject moves.

The control panel contains multiple buttons to give users full control over the test progress. The buttons allow the user to select a subject from the database and some options about the selected test (e.g. the leg whose angles will be measured or the type of ankle eversion). The start and stop buttons trigger the

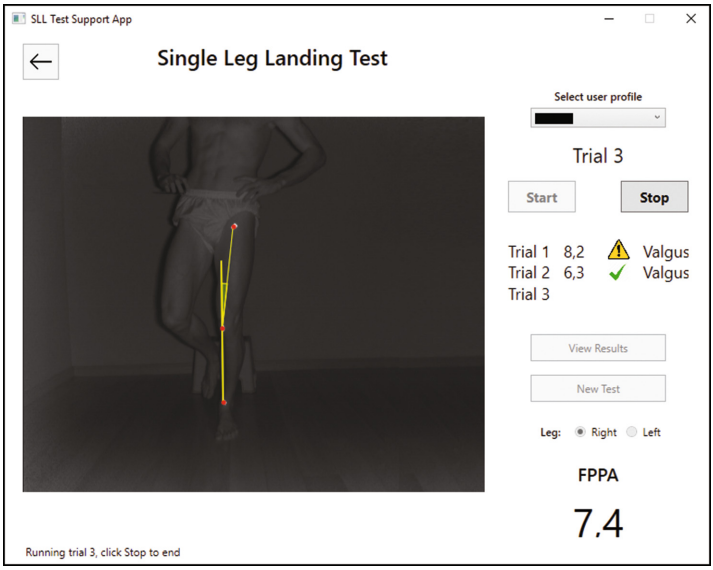

Fig. 4. System application snapshot: SLL test window [15]

respective stages of the test. During the test performance, the angles are shown at runtime and each frame value is stored. If a marker is not properly detected during a frame, it is not displayed and the angle value is not computed. The system gives users the chance to perform up to 3 attempts in each test, in order to repeat those attempts whose performance could be doubtful. Whenever the user stops the test, individual information is offered for each attempt, being possible to visualize a plot of all data captured during the test and the evolution of the angle value (Fig. 5). This feature allows experts to go further than just analysing the value at the maximum flexing point (as it is done with offline video analysis tools). However, an offline analysis of the data is also allowed, since the data is also written on a comma-separated values file (.csv).

The status bar shows both sensor connection state and overall progress test. The control panel is disabled until the sensor becomes available, to avoid possible errors. An historical representation of the data can be also displayed on a chart for each leg and angle type in order to inspect the subject's angle evolution along time.

3 Validation

In order to check the reliability of the developed system it has been validated against a 2D offline video analysis software whose use is very extended, Kinovea software [17]. This software allows the user to analyze previously recorded video frames, running them at slow motion and freezing the video at the desired frame. Once the video has been frozen, the user can place manually lines and markers

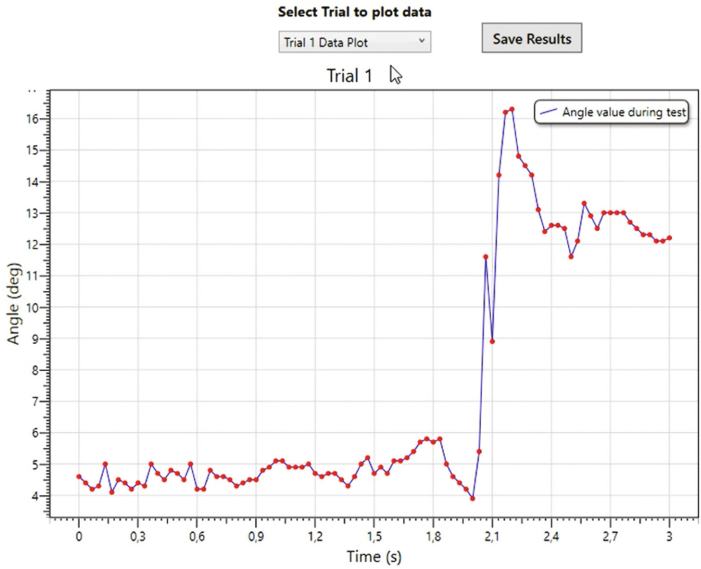

Fig. 5. SLL test data

over the image, and the software returns the angle between the lines. In that way, joint angles can be measured relying on the physical markers placed over the subject's body. 2D video analysis tools have been applied in many studies, and contrasted against 3D techniques [18,19]. Allan G. Munro et al. [20,21] also showed the reliability of 2-D techniques when assessing knee injury risk and established measurement error values for this type of analysis.

There exists a great range of tests on which knee alignment can be measured, regardless of the physical condition of the assessed subject. Most-widely used ones are single leg squat (SLS) [5,18,22], drop vertical jump (DVJ) [8], drop landing (DL) [23] and single leg landing (SLL) [24], as they simulate real movements and interactions produced during sport practice. In this work, the SLL test has been implemented, due to its promptness and simplicity, saving time to experts and making it easier for subjects to understand the procedure. In order to perform the test, the method proposed in [23] is followed and explained in the following paragraph.

In order to simulate the landings encountered during athletic participation, the SLL test requires the subject to perform a unilateral step landing task. This involves stepping off a 30-cm-high bench landing with the opposite leg onto a mark positioned 30 cm from the bench, and holding on the position for at least 2 s. During the test, subjects have to keep the hands on their hips and ensure that the contralateral leg makes no contact with any other surface. The sensor is placed at the subject's knee level, 2 m away from the landing target and aligned perpendicular to the frontal plane. It is recommended to perform various landings with each leg, and

the final FPPA value should be measured based on them. Three reflective markers must be strictly attached at the anatomic points proposed in [5]: (i) Anterior Superior Iliac spine, (ii) middle of tibiofemoral joint and (iii) middle of ankle mortise. The markers alignment draws two lines, whose frontal projected angle is recorded as FPPA and is measured at the maximum flexing point. If the knee moves to the subject's sagittal plane, it is known as knee valgus; if it moves outside, it is known as knee varus [25].

To perform the study, ten volunteers, five males and five females were recruited to be evaluated in a Single Leg Landing (SLL) test by a external physical therapist using both Kinovea and the proposed system. Before performing the evaluation, the subjects were informed about the research aims. The execution of the test was recorded simultaneously with the Kinect sensor and with a digital color video camera, one placed above the other with the minimum sensor displacement. The SLL test procedure was explained to the subjects before starting and each of them perform three attempts with a rest time of 30 s. With the proposed system, the FPPA value was automatically obtained, and with the Kinovea software, the recordings had to be analyzed after the experiment by the same physical therapist who directed the test.

The evaluation aims at estimating the inter-rater reliability between both measurement systems. The results of each patient in each attempt are gathered in Table 1. As it can be observed, both results are generally similar. To support this observation, a formal statistical analysis has been performed using the intraclass correlation coefficient (ICC)(ρ) [26]. The results have been extracted using R software v.3.3.2. The one-way random effects ICC(ρ) obtained is **0.996** and its 95% confidence intervals (CI) are **0.984–0.999**. According to [27], values higher than 0.9 reflect excellent reliability.

Table 1. Case study results. Angle values are expressed in degrees (°).

Patient ID	1	2	3	4	5	6	7	8	9	10
Age	26	22	21	23	36	18	31	25	32	24
Trial 1 (S)	12.4	13.5	14.9	14.1	18.7	20.2	10.8	9.7	13.4	17.1
Trial 1 (K)	12	14	15	14	18	21	12	9	13	17
Trial 2 (S)	17.6	21.4	12.8	15.1	15.8	16.2	6.7	12.6	15	21
Trial 2 (K)	18	22	14	16	16	17	5	12	15	21
Trial 3 (S)	18.5	16.3	9.6	23.3	18.2	17.4	8.5	8.7	12.4	18.7
Trial 3 (K)	18	16	10	23	18	17	8	9	12	19
Average (S)	16.2	17.1	12.4	17.5	17.6	17.9	8.7	10.3	13.6	18.9
Average (K)	16	17.3	13	17.7	17.3	18.3	8.3	10	13.3	19

(K) Kinovea - (S) Proposed system

Although the results of the study are promising, a study including higher number of participants and different measurements would be required to further confirm this findings.

4 Conclusions

Offline 2-D video analysis is an extended method to quantify knee FPPA. However, this procedure requires large time investments. In this paper we have presented an automatic 2-D video analysis system to support experts during joint angles measurement. The process involves using a depth sensor to track the position of retro-reflective markers attached to the subject's joints. The angles are dynamically measured based on the marker's position.

The comparison between both systems leads us to conclude that the agreement between them is very high, and the reliability of the measurements obtained through the proposed system is excellent. A study including higher number of participants and different measurements and a comparison with 3D motion capture systems will be performed soon and could lead to an extended version of this paper.

Given the promising results of the validation, we are working on the implementation of an autonomous system for injury prediction and performance status evaluation through machine learning, as described in Sect. 1.

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