ORIGINAL ARTICLE

App for motion analysis: pilot study

Uso de aplicativo para análise de movimento: estudo piloto

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ABSTRACT

Alternative and low-cost measures may be important for analyzing human movement. **Objective:** The objective of this study was to verify the agreement of human movement analysis of a monitoring app that uses artificial intelligence compared to three-dimensional movement analysis. **Methods:** Observational cross-sectional case report study in which a healthy volunteer performed arm flexion, elbow flexion, trunk flexion, lateral trunk bending, and sitting and standing. Images of the volunteer were simultaneously captured by a three-dimensional movement analysis system based on infrared cameras and the *Linkfit* app of two mobile devices (smartphones). The body angles estimated by the *Linkfit* app were compared with the corresponding angles measured by the three-dimensional movement analysis system. The Granger causality test was used to compare the pairs of angles for each parallel data series. **Results:** The use of smartphone cameras and deep learning techniques for motion detection had an 84% degree of agreement compared to measurements generated by the three-dimensional movement analysis performed in the laboratory. **Conclusion:** The use of smartphone cameras and deep learning techniques is promising for conducting studies for body movement detection compared to the gold standard measures of movement analysis. This technology may become an alternative for movement analysis. Future studies should consider a more significant number of volunteers and model movements to strengthen the results obtained in this study.

Keywords: Movement, Smartphone, Telemedicine

RESUMO

Medidas alternativas e de baixo custo podem ser importantes para análise do movimento humano. **Objetivo:** Verificar a concordância de análise de movimento humano entre aplicativo de monitoramento por meio de inteligência artificial com análise tridimensional de movimento. **Método:** Estudo transversal observacional no qual voluntário sadio realizou movimentos de: flexão dos braços, flexão de cotovelos, flexão de tronco, inclinação de tronco e sentar e levantar. As imagens foram captadas por meio de sistema de análise tridimensional do movimento por câmeras infravermelhas e pelo aplicativo da *Linkfit* por meio de dois dispositivos móveis (smartphones). Foram comparados os ângulos estimados pelo aplicativo da *Linkfit* com os ângulos correspondentes medidos pelo sistema de análise tridimensional do movimento. Para comparar os ângulos da *LinkFit* com os ângulos mensurados pelo laboratório tridimensional de movimento, o teste de causalidade de Granger foi usado para cada série paralela dos dados. **Resultados:** A utilização de técnicas de visão computacional e deep learning para detecção de movimento utilizando câmeras de celular mostrou um grau de concordância de 84% em relação à medidas geradas por análise tridimensional de movimento realizadas em laboratório. **Conclusão:** A utilização de técnicas de visão computacional e deep learning é promissora para a realização de estudos que envolvem a detecção do movimento do corpo humano, quando comparadas com medidas de padrão-ouro de análise de movimento, podendo ser portanto, uma alternativa. Estudos futuros devem ser realizados utilizando maior número de voluntários e movimentos, com o intuito de consolidar os resultados obtidos nesse estudo.

Palavras-chaves: Movimento, Smartphone, Telemedicina

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INTRODUCTION

The human movement encompasses several functions such as walking, executing simple daily activities such as personal hygiene, or even the complex and fine movements of high-performance sports. It bears complexity due to the various sensorimotor interactions that it demands.[1,2]

The development of motion assessment methods to improve accuracy and reliability has yielded useful investigative tools in various areas of research and clinical practice of rehabilitation, ergonomics, sports, and others.[3]

The principle of analyzing the human body movement via images consists of capturing a sequence of photos (photogrammetry) with one or more cameras, obtaining position and orientation data of the whole body or parts of interest by measurements conducted on these images. Three-dimensional motion analysis may be unfeasible in the clinical environment because it requires ample physical space, complex equipment, the experience of professionals for data collection and analysis, not to mention its high cost.[4]

Recently, new smartphones applications (apps) are also proposing to assess body movement.[4] A systematic review and meta-analysis on the validity and reliability of smartphones apps for assessing spinal kinematics concluded that it is currently possible to use smartphones to measure the range of motion of cervical flexion and extension, lateral flexion, and lumbar flexion. Also, smartphones can evaluate the thoracic region and lumbar extension. However, they report that more studies are needed for the safe use of these instruments as evaluation methods.[4] Another study stated that smartphones and apps are important tools for health care; however, they are used without thoroughly understanding their risks and benefits. Furthermore, rigorous evaluation, validation, and development of best practices for healthcare applications are necessary to ensure a proper level of quality and safety when these tools are used.[5]

Recently, *LinkFit* developed an app with a series of available physical activities, in which artificial intelligence and computer vision algorithms monitor and correct movements in real-time.

The Openpose algorithm[6] is used to obtain the positions of anatomical points during exercises according to images obtained by a smartphone camera. The trajectories of these anatomical points are analyzed through a specially developed algorithm, allowing the orientation and correction of the exercises during their execution and the subsequent analysis by the prescribing professional. It is essential to guarantee the reliability of the anatomical spots obtained by this method, once they are the basis for the correct assessment of the exercises being performed.

OBJECTIVE

The objective of this study was to verify the agreement of the human movement assessment performed by the artificial intelligence monitoring app compared to a three-dimensional movement analysis conducted in a laboratory.

METHODS

This pilot study was conducted under the principles of the Declaration of Helsinki. A male volunteer, staff from the rehabilitation center in which this study was carried out, authorized his participation, which consisted of capturing his movement images. The individual was healthy and did not have musculoskeletal pain or neurological alterations that could hinder the performance of the requested movements.

The volunteer was asked to perform the following movements to capture the movements, as instructed during data collection: 1. arms flexion - raise the extended arm, close to the body, starting the movement with the extended arm downwards, and ending with the extended arm upwards; 2. elbow flexion - with the elbow fixed to the body, flex the forearm; 3. trunk flexion - touch the tips of the fingers in the tips of the toes, without bending the knees; 4. lateral trunk bending - with the arms close to the body and downwards, incline the trunk to the right and then to the left; 5. sit and stand - with the help of a chair, sit and stand without flexing the spine. Five repetitions of each movement were performed and recorded. Chart 1 shows the angles analyzed for each movement performed by the volunteer.

Chart 1. Movements and angles assessed for each movement

Movement	Region of interest	Angle of interest
Arms flexion	Arm and forearm	L_ELBOW
Elbow flexion	Arm and forearm	FRONT_ELBOW
Trunk flexion	Trunk	BACK_HIP, FRONT_HIP
Trunk lateral bending	Trunk	SHOULDER, BACK_HIP, FRONT_HIP
Sit and stand	Spine and lower limbs	BACK_HIP, FRONT_HIP, BACK_KNEE, FRONT_KNEE

To capture the volunteer's movements, the three-dimensional movement analysis system installed at the Vila Mariana Unit of the Instituto de Medicina Física e Reabilitação do Hospital das Clínicas da Faculdade de Medicina da Universidade de São Paulo (IMREA/HCFMUSP) was used as the gold standard.

This system comprises eight infrared cameras model Oqus® 300 and 2 hybrid cameras (infrared and color video) model Oqus 210c from Qualisys AB (Sweden), connected to a computer with the Qualisys Track Manager® software version 2.11. This software reconstructs the three-dimensional trajectories of reflective spherical markers applied to the volunteer's body. Twenty-one markers were applied to anatomical points according to the modified Helen Hayes protocol:[7] anterosuperior iliac spines, sacrum, lateral sides of the thighs (distal third), lateral condyles of the femurs, lateral faces of the legs (proximal third), lateral malleolus, calcaneal and second metatarsal heads, acromion, lateral humeral epicondyles, midpoints between the styloid processes of the radius, and ulna. The three-dimensional coordinates of these markers were recorded at a frequency of 100Hz.

Subsequently, the Orthotrak® software version 6.2, from Motion Analysis Corporation (USA), was used to calculate the anatomical points' three-dimensional trajectories, i.e., the joint angles that would be compared to those obtained by the app.

To capture the movements by the *Linkfit* app, two mobile devices, one branded Xiaomi® Mi 9 SE with a 48MP camera and a Motorola® G5S Plus with a 13MP camera, were positioned respectively in front (anterior) of and to the side (lateral) the volunteer, capturing the images at a rate of 30 frames per second. With the Openpose[6] algorithm, which uses deep learning techniques for posture inference, it was possible to capture the 2D position of 18 anatomical points - eyes, ears, nose, neck, shoulders, elbows, wrists, hips, knees, and feet. 13 angles were calculated from these points, as described in Chart 2.

Chart 2. Angles of interest, description, and camera position

Angle name	Description	Camera position
FRONT_HIP	Anterior view angle formed by the shoulder, hip, and knee	lateral
BACK_HIP	Posterior view angle formed by the shoulder, hip, and knee	lateral
R_HIP	Right lateral view angle formed by the shoulder, hip, and knee	anterior
L_HIP	Left lateral view angle formed by the shoulder, hip, and knee	anterior
FRONT_KNEE	Frontal view angle formed by the hip, knee, and ankle	lateral
BACK_KNEE	Posterior view angle formed by the hip, knee, and ankle	lateral
R_KNEE	Right lateral view angle formed by the hip, knee, and ankle	anterior
L_KNEE	Left lateral view angle formed by the hip, knee, and ankle	anterior
FRONTAL_ELBOW	Frontal view angle formed by the shoulder, elbow, and wrist	lateral
BACK_ELBOW	Posterior view angle formed by the shoulder, elbow, and wrist	lateral
R_ELBOW	Right lateral view angle formed by the shoulder, elbow, and wrist	anterior
L_ELBOW	Left lateral view angle formed by the shoulder, elbow, and wrist	anterior
SHOULDER	Right lateral view angle formed by the shoulder, neck, and x-axis	anterior

A pairing was made between the angles generated by the *Linkfit* app and the corresponding angles measured at the three-dimensional movement analysis laboratory to enable the comparison, as shown in Chart 3.

Data preparation

Several techniques were applied for comparing the data generated by *Linkfit* and that from the laboratory. The researchers dealt with different biases, spatial references, and data acquisition frequency. The flow used in this step is shown in Figure 1.

Recordings made by the laboratory and *Linkfit* were extracted at different frequencies (Hz). Therefore, for direct comparison, the laboratory data were re-sampled. The values of both measurements were normalized for amplitude and series interpolation was applied for missing values. To reduce the noise of the series, the lfilter algorithm, by the scipy library https://docs.scipy.org/doc/scipy/reference/generated/scipy.signal.lfilter.html , was used. The Finite Impulse Response filter (FER), with coefficient in the numerator equal to [1.0 / n] * n, where n= 31, and the vector of the coefficient of the denominator with value 1 was applied. Outliers were removed

Chart 3. Equivalence between the angles generated by the *Linkfit* app and those generated at the movement analysis laboratory

Linkfit app angles	Movement analysis laboratory angles
FRONT_HIP	L_HIP Flex ANG
BACK_HIP	R_HIP Flex ANG
R_HIP	R_HIP Abd ANG
L_HIP	L_HIP Abd ANG
FRONT_KNEE	L_KNEE Flex ANG
BACK_KNEE	R_KNEE Flex ANG
R_KNEE	R_KNEE Abd ANG
L_KNEE	L_KNEE Abd ANG
FRONTAL_ELBOW	L_Elbow_Ang
BACK_ELBOW	R_Elbow_Ang
R_ELBOW	R_Elbow_Ang
L_ELBOW	L_Elbow_Ang
SHOULDER	Trunk_Lat_Tilt

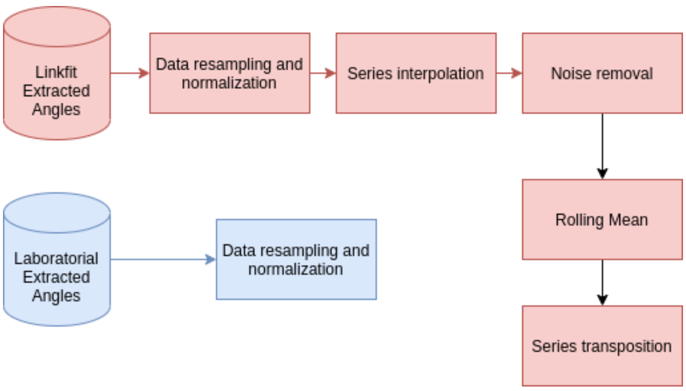

Figure 1. Data collection and preparation flow for image analysis

with the rolling mean of the series. To correct and match the start of the lab and *Linkfit* recordings, we transposed the time series of the *Linkfit* data, combining the two global maxima from each series.

Data analysis

To compare the angles measured by *Linkfit* to the angle measurements of the laboratory, the Granger Causality test was used for each combined series. The Granger test is widely used for predicting time series. In this study, we hypothesize that knowing that both methods measure the same event with the same objectives, they should be the same in the optimal case, therefore, the causality should be maximum. A Granger test was implemented for each series and its angles, accepting the null hypothesis (where one series does not g-cause the other), with a p-value of 0.005. Finally, we calculated the number of times in which hypothesis one was denied – where one series g-causes the other – divided by the total amount of series.

RESULTS

The results obtained in this study show a suitable causal relationship between the angles captured by the gold standard, which was the three-dimensional analysis of movement at a movement laboratory and the software proposed by *Linkfit*.

Table 1 shows, for each angle analyzed, the percentage of times the Granger causality was positive, i.e., the null hypothesis was rejected.

Table 1. Frequency of positive causality for the analyzed angles

Angle	% of g-causes
FRONT_HIP	75%
BACK_HIP	83%
FRONT_KNEE	80%
BACK_KNEE	100%
L_ELBOW	75%
FRONT_ELBOW	80%
SHOULDER	100%
Mean	84%

As presented previously, each exercise was used to measure specific body angles. Therefore, considering the arm and the forearm, we found 75% for L_ELBOW and 80% for FRONT_ELBOW (causality average of 77.5%) during the exercises of arm flexion and elbow flexion. Considering the trunk, we found 75% for FRONT_HIP, 83% for BACK_HIP, and 100% for SHOULDER (causality average of 86%) during trunk flexion exercises and lateral trunk bending. Regarding spine and lower limbs, we found 75% for FRONT_HIP, 83% for BACK_HIP, 80% for FRONT_KNEE, and 100% for BACK_KNEE (causality average of 84.5%), during the sit to stand exercise.

DISCUSSION

Movement is an essential aspect of human life. It is essential for various daily activities such as locomotion, feeding, work, and physical or sports activities. It is known that the individuals move to obey the demands of any task being realized within a specific environment.[1]

During sports practice or any physical activity, the correct movement must be performed so that the activity effectively promotes gains, without adverse events such as injuries that the wrong posture can cause during the execution of specific movements. Therefore, in this study, the comparison between the movement analysis performed by a movement laboratory and the measurements performed by the smartphone app becomes very important. Although this study is a case report, our results show promising course smartphone cameras combined with machine learning and deep learning models for motion analysis in a more accessible way.

Despite the algorithm's limitations, the use of cell phone cameras should bring great accessibility to motion analysis solutions. Consequently, this technology may help identify difficulties in executing movements or even aid the assessment of diseases in which movement is compromised. The agreement observed between the movement analysis performed by the gold standard (three-dimensional movement laboratory) and the *Linkfit* app is relevant once it is possible to infer that the adjustments suggested by the app's artificial intelligence during the execution of the movements are based on reliable measurements. Therefore, safety and efficiency in executing movements can be adequately provided.

Our results agree with a review on the use of smartphones for motion analysis. This review concluded that these devices demonstrated relevant capability as non-invasive motion monitoring. Furthermore, studies have shown that when movement detection components are used, the device can estimate various movements with potential applications for healthcare.[8]

These results are also compatible with those obtained in a study that compared motion analysis algorithms by video cameras, including Openpose, to a reference method with markers in a three-dimensional movement analysis laboratory.[9] In that study, systematic differences were obtained in the calculated positions of joint centers that ranged from 1mm to 50mm, depending on the joint and movement studied. They concluded was that, regardless of the reliability limitations of their data, the image analysis methods without body markers are promising for applications in environments outside the laboratory, provided that these limitations are resolved.

Some limitations of the present study include the inclusion of only one volunteer and a restricted set of simple movements and the need for adjustments to allow comparison between measurements made by different instruments. Nonetheless, this methodology allowed the verification of reasonable compatibility between the measurements obtained by both systems. Consequently, the potential for using a technique that is easier to access than the traditional method of a three-dimensional movement analysis laboratory could be stated.

Therefore, future studies to analyze apps the reliability of apps to evaluate performances of more complex movements or even verify the effectiveness of exercise programs guided by this type of system are essential and desirable.

CONCLUSION

This study concluded that the angles measured by images captured with smartphone cameras, if processed as described in the methods described in this study, could be effectively compared with measurements of a three-dimensional movement analysis laboratory 84% of the time.

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