Medical Hypotheses 142 (2020) 109741

Contents lists available at ScienceDirect

Medical Hypotheses

journal homepage: www.elsevier.com/locate/mehy

Can human posture and range of motion be measured automatically by smart mobile applications?

Rayele Moreira[a,c,*], Ariel Teles[a,b,d], Renan Fialho[a], Thalyta Cibele Passos dos Santos[a], Samila Sousa Vasconcelos[c], Itamara Carvalho de Sá[c], Victor Hugo Bastos[a], Francisco Silva[d], Silmar Teixeira[a]

[a] *Federal University of Piauí, Parnaíba, PI, Brazil*
[b] *Federal Institute of Maranhão, Araioses, MA, Brazil*
[c] *University Center Inta – UNINTA, Sobral, CE, Brazil*
[d] *Federal University of Maranhão, São Luís, MA, Brazil*

ARTICLE INFO

Keywords:
Human postural assessment
Spinal misalignment
Mobile
Applications
Wearable devices

ABSTRACT

Human posture and Range of Motion (ROM) are important components of a physical assessment and, from the collected data, it is possible to identify postural deviations such as scoliosis or joint and muscle limitations, hence identifying risks of more serious injuries. Posture assessment and ROM measures are also necessary metrics to monitor the effect of treatments used in the motor rehabilitation of patients, as well as to monitor their clinical progress. These evaluation processes are more frequently performed through visual inspection and manual palpation, which are simple and low cost methods. These methods, however, can be optimized with the use of tools such as photogrammetry and goniometry. Mobile solutions have also been developed to help health professionals to capture more objective data and with less risk of bias. Although there are already several systems proposed for assessing human posture and ROM in the literature, they have not been able to automatically identify and mark Anatomical and Segment Points (ASPs). The hypothesis presented here considers the development of a mobile application for automatic identification of ASPs by using machine learning algorithms and computer vision models associated with technologies embedded in smartphones. From ASPs identification, it will be possible to identify changes in postural alignment and ROM. In this context, our view is that an application derived from the hypothesis will serve as an additional tool to assist in the physical assessment process and, consequently, in the diagnosis of disorders related to postural and movement changes.

Introduction

The concept of symmetry between hemibodies does not apply to the human body because the viscera and internal organs such as intestines, stomach, liver and heart do not divide equally between right and left sides of the body [1]. Although human body is not perfectly symmetrical, we can say that it is phenotypically similar between the two homebodies that form it and, therefore, exaggerated discrepancies may represent functional changes for an individual [2]. As an example, we can examine the functional performance of an individual with amputation of one of the lower limbs. In this person, the first function affected by discrepancy in limb size is the balance. In addition, posture and gait are affected [3] and even manual tasks might be compromised, as any movement with the hands may cause trunk displacement, which may lead to falls. Discrepancies in leg size also can trigger angular deformities of the spine [4], muscle contractures and even conditions such as degenerative arthritis in the lower extremity and lumbar spine [5].

Since exacerbated asymmetries may trigger structural changes in the human body and compromise its functionality [2] (e.g., by interfering with gait, manual tasks, posture), the sooner these asymmetries in the limbs are identified, the earlier the intervention will be to correct them. Therefore, analysing them should be part of the assessment procedures of health professionals who work with human functionality, such as physicians, physiotherapists and physical educators [6]. In this sense, different instruments and assessment methods are used by health

* Corresponding author at: Universidade Federal do Piauí, Programa de Pós-graduação em Biotecnologia (RENORBIO). Technological Neuronovation & Brain Mapping Laboratory (NITLAB). Av. São Sebastião no 2819 –Nossa Sra. de Fátima, Parnaíba, PI CEP: 64202-020, Brasil.

E-mail addresses: rayelemoreira@ufpi.edu.br, rayele.moreira@uninta.edu.br (R. Moreira), ariel.teles@ifma.edu.br (A. Teles), victorhugobastos@ufpi.edu.br (V.H. Bastos), fssilva@lsdi.ufma.br (F. Silva), silmarteixeira@ufpi.edu.br (S. Teixeira).

https://doi.org/10.1016/j.mehy.2020.109741
Received 22 February 2020; Received in revised form 23 March 2020; Accepted 11 April 2020

professionals to identified and measure Anatomical and Segment Points (ASPs) [7]. ASPs are specific points on the body (e.g., scapular acromion, anterior superior iliac spine, major and minor trochanter, epicondyle, malleolus), while anatomical segments are represented by the area of distance between two anatomical points (e.g., the distance between shoulder and anterior superior iliac spine). Examples of assessment methods include the lower limb size assessment with a tape measure, postural assessment, and goniometry [8].

Assessment of asymmetries in limb size is mainly performed manually and visually, that is, the assessor manually identifies anatomical points, and visually seeks to identify discrepancies between them. To assist in screening patients with discrepancies in the length of the lower limbs, the "direct" clinical method [5] is considered efficient, although it is not as accurate as imaging methods. In this method, a measuring tape is used to measure the length of each lower limb by measuring the distance between the anterior superior iliac spine and the medial malleolus. For postural assessment, anatomical points assessed in the direct clinical method are also identified and, in addition to them, other points, such as knee, elbow, wrists and shoulders, are used as reference points for identifying postural deviations [9]. In the goniometry, anatomical points are also used as a reference, but the first step in this method is to identify the axis of the joint. Next, fixed and mobile segments are identified, and then joint Range of Motion (ROM) is measured [10]. In addition to goniometry, measures of size and proportions of the body (i.e., anthropometry or perimeter) are also useful for identifying body asymmetries and functional adaptation of the human beings to the environment where they live.

Whereas various types of technologies have been applied to improve diagnostic methods in health, different models of photogrammetry software for identifying Anatomical and Segment Points (ASPs) have also been developed, especially those ones applied to postural assessment [11,12]. They include, for example, the *Posture Assessment Software* (in Portuguese, *Software de Avaliação Postural - SAPO*), the *Digital Image-based Postural Assessment Software - DIPA*) [13], and the Posture Pro [14]. Such software solutions enable to measure the size of anatomical segments, but still require the marking of ASPs to be performed manually by assessors. The difference between these systems and direct clinical method is because reflective markers are fixed at the human anatomical points to facilitate their visualization in the patient's photographs, which are analyzed by the systems.

New advances in image-based software solutions, which analyze and process images, have already been developed and applied to identify ASPs, at the same time that mobile applications have been used for goniometric assessment [15,16] and postural [17] assessments. In application stores such as Play Store and Apple Store, it is possible to find a variety of solutions that promise to be useful in helping health professionals with these assessment procedures. In the literature, the PostureScreen [18] stands out as a mobile solution that identifies APSs digitally in a process made directly on the mobile device screen, which still needs to be done manually [19]. However, we have not identified any system capable of performing the identification of anatomical points in a fully automatic way.

Although we have not found solutions with this functionality, recently, an open source library launched by Google, named *TensorFlow* [20], which includes robust machine learning (ML) algorithms that, along with *PoseNet* computer vision (CV) model [21], automatically identify ASPs. These technologies can be applied to automatic identification of ASPs, contributing with the optimization of musculoskeletal assessment. However, these software solutions have not yet been used for the development of mobile applications for human posture and ROM assessments.

Hypothesis

We hypothesize that it is possible to develop a mobile application embedded with ML algorithms and CV models to automatically measure human posture and ROM. We believe that software solutions proposed for these tasks can assist health professionals in the clinical assessment and diagnosis process of changes in the joint ROM and postural deviations. Fig. 1 presents an overview of the hypothesis. Blue boxes are the basic concepts for supporting the hypothesis: mobile computing, which represents the powerful capabilities of the current mobile devices, and artificial intelligence, which acts as a broker for the revolutionary popularization and evolution of ML algorithms. Red boxes are the domains in which the hypothesis permeates: ROM, which is the amount of joint movement (measured in degrees) performed by an individual actively or passively, and posture assessment, which includes analyzes of spinal alignment.

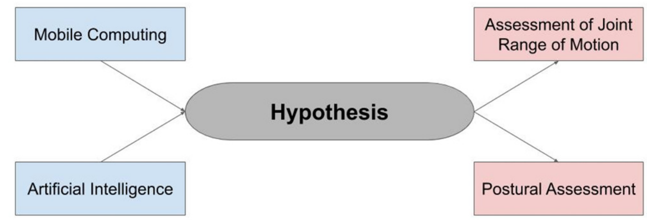

Fig. 1. Overview of the hypothesis.

Support for the hypothesis

The integration between the human being and machine is a condition present in people's daily lives. At street, at home, at work, everywhere, we can see how machines integrate the human environment and collaborate with the improvement of productive and social processes. This integration becomes even more specific with advances in the fields of Artificial Intelligence (AI) and Mobile Computing, both of them already widely used in different health areas.

Artificial intelligence is a modelling of intelligent behavior using a computer with minimal human intervention and applied to solve complex problems [22]. ML algorithms can be seen as a means to achieve the AI concept. Supervised and unsupervised learning [23] are approaches in which ML algorithms are classified. Different ML algorithms have been proposed and used in scientific health research, such as decision trees, support vector machine, neural networks, and convolutional neural networks (i.e., deep learning), and perform different tasks such as classification, regression, clustering and prediction [24]. There are a variety of proposed methods that use ML algorithms as solution to deal with complex health problems, such as detecting Alzheimer's disease [25], predicting stroke [26], and predicting therapeutic outcomes in depression [27]. Specifically in medical image processing, we can mention as application examples: detection and classification of knee arthroplastys [28], detection of bone maturity [29], analysis of images of human tissues and organs (e.g., magnetic resonance imaging, ultrasound imaging, X-ray) and also to assist in the diagnosis and monitoring of diseases such as cancer [30].

ML algorithms are also used in the analysis of kinematics and body biomechanics [31], as well as physiological demands during sports practice [32]. From these analyzes, it is possible to identify failures in body movement and adjust it to improve motor performance. Kinematics data, associated with data on human body posture, also help predicting the occurrence of motor development failures in infants and, indirectly, identify risk of neurological disorders such as cerebral palsy and autism spectrum disorders [33]. Indirect prediction of the neurological disease based on kinematic analysis and postural control using ML algorithms was also applied to the diagnosis of Alzheimer's disease [34]. That is, these algorithms can also be useful as indirect method for diagnosing other diseases from the analysis of data about human movement and posture [34].

As highlighted, analysis of human movement and posture can support in the diagnosis of diseases related to body joints, as well as diseases that affect other human organs and tissues. Since these analyzes can provide data to assist in the diagnosis of diseases, it is necessary to develop reliable methods to assess and identify structural and functional changes in human movement and posture. In order to perform this analysis, firstly, it is necessary to estimate body position and this is done based on the identification of ASPs. To do that, software solutions for biophotogrammetric analysis and computerized motion analysis are developed. However, this analysis is dependent on the palpation performed by the assessor [13,14]. That is, the assessment is dependent on the experience of the health professional to manually identify the ASPs. To reduce the chance of measurement bias, new methods are being developed for the assessment process.

Human [35] and animal [36] pose estimation based on the identification of ASPs is now automatically performed by ML algorithms. It does not depend on the manual identification performed by the professional. These assessments inherent in the medical and health sciences are now optimized and improved by incorporating CV models with ML algorithms that are trained to recognize, interpret and classify varied data sets. In addition, ML technologies can now be integrated with multiple platforms, including mobile devices [37]. This compatibility with mobile device platforms may favor the incorporation of ML technologies into devices used routinely by people, such as smartphones.

Smartphones are not just a simple voice communication device. These devices are increasingly robust, integrating high computational power (i.e., processing, memory and storage), high resolution cameras, and connectivity with different wireless interfaces. Due to these characteristics, such devices are now capable of integrating different technologies, such as ML algorithms, CV models and sensors (e.g., accelerometer, gyroscope, magnetometer). The functional evolution of these mobile devices has made them a widely used tool in data transmission (e.g., messages, audios, photos, videos). This great capacity to store and transmit data in a fast and practical way, as well as the ease of access and handling by the user, made smartphones to be used in various tasks in people's daily lives. Following these advances in mobile computing, computer and health professionals have combined their background knowledge and practical needs for developing mobile solutions to assess and monitor human health, and assist diagnostic processes as well as encouraging physical activity [38,39].

By offering a computing environment that supports increasingly robust technologies, smartphones have been used in medical field and health sciences as an auxiliary device in evaluative and therapeutic processes. Recent applications include monitoring patients with depression [40], managing illnesses [41] and assisting with surgical procedures [42]. In addition to these applications, by combining sensor technology and image analysis, mobile devices have also been used by health professionals as a tool in physical assessments, including assessing gait [43] and evaluating movement and therapeutic exercises performed by patients [44,45], especially outside the clinical environment. Thus, they help doctors or other health professionals to monitor the frequency, type and intensity of exercises [45,46].

Regarding the analysis of ROM using goniometry, the instrument traditionally used is the universal goniometer [47]. However, mobile applications have now been used as an alternative method for this assessment process [15] and a variety of mobile applications are being developed to assess the ROM [48]. Accompanying this evolution in the evaluation process of the human body, other applications for smartphones are also found in the literature, whose function is to assist in the postural assessment of people and identify anatomical changes that interfere with posture alignment (e.g., scoliosis, hyperkyphosis, hyperlordosis) [49,17,19].

Opposition to the hypothesis

Internal structures that help shaping the human body appear to be more complex, however, they are organized in a very manageable environment, allowing a set of images to be generated for training a deep learning model [50]. Externally, human body seems less complex, however, the identification of specific ASPs may be more difficult, since there are several APSs with different characteristics distributed throughout the body (e.g., shoulder, wrist, iliac spine, ankle). Moreover, these ASPs are covered by various tissues as skin, muscles and fascias. All these factors can hinder the external visualization of the ASPs [51,36]. Therefore, it is necessary to overcome these anatomical "barriers" for recognizing ASPs [35]. Given this, a point that can make this hypothesis unviable is the possibility that a mobile application can not be able to identify the APSs commonly used in other systems such as wrist, iliac spine, malleolus, whose identification is facilitated by the use of reflective markers positioned on them. Consequently, they will not allow to measure the distance between APSs. However, deep learning solutions (e.g., *DeepPose* [35], *PoseNet* [21,52] and *MediaPipe* [53]) have already shown that it is possible to identify ASPs, thus overcoming these possible limitations.

Once this limitation is overcome, another factor that can oppose the hypothesis presented here is the impossibility of integrating ML and CV technologies into smartphones. However, considering the advances in computational power and connectivity that these mobile devices have undergone, they already have supported deep learning algorithms such as those ones embedded in the *TensorFlow* library [54].

Assuming that mobile applications for measuring automatically human posture and ROM can overcome these aforementioned barriers, another opposition is the possible mistrust regarding the precision in the identification of ASPs, as well as the measures of the distance between them. However, ML algorithms are already capable of automatically calculating their confidence score. In addition, experimental evaluations may be performed to measure different metrics such as precision, recall, accuracy and F-score, which are usual measure of success for ML algorithms [55,56]. Applicability of mobile systems as a method for measure human posture and movement may also be questioned to be used in in clinical settings. However, this is an opposition that can only be refuted or not when a mobile system that integrates technologies embedded in the smartphones with ML algorithms is developed and made available to be used by health professionals for assessments.

Initial evaluation of the hypothesis

New more robust ML technologies have been developed and, recently, Google Research Team have developed *TensorFlow* [20,54], a open-source library for AI and Numerical computation. This library is considered a robust solution that allows software developers to easily train and implement ML models [20]. It can offer flexibility for large quantitative algorithms, portability, and support for mobile devices. Among the advantages of this system, it is possible to highlight that it can be run on several platforms, including in mobile systems such as Android and iOS [37]. Among the deep learning frameworks supported by *TensorFlow* is the *PoseNet* package [21,52], a recent framework developed to estimate human position from the identification of its joints. That is, determining the position of different ASPs by using one or several images [57]. This solution enables 2D skeletal tracking to be performed through a web browser and camera, embedded in computers, tablets or smartphones [58]. *PoseNet* is applicable in all situations involving positioning and tracking of body position. By integrating *PoseNet* with technologies embedded in smartphones, it becomes possible to implement a mobile application for identifying ASPs and measuring the size of segments. Hence, mobile applications may be used to measure and assess ROM and human posture.

To test the feasibility of our hypothesis, we developed a mobile application prototype and embedded both *TensorFlow* and *PoseNet* in it. To do this, we used the Ionic Framework [59], which is an open-source toolkit for building cross-platform mobile and desktop applications. The main functionalities of the prototype are organized into three parts: (i)

Image Capture; (ii) Estimate Human Position on Image; and (iii) Data Result on Image. The image capture was developed with Camera Preview Library available on the Ionic Native Plugin developer package.

In the point estimations, the captured photo is submitted to the *PoseNet* function net.estimatePoseOnImage(). “net” is a pre-defined configuration with the following parameters: (architecture: MobileNetV1, outputStride: 16, inputResolution: [width, height] and multiplier: 0.50).

The chosen artificial neural network architecture was *MobileNetV1* because it is soft and, hence, suitable to be used in mobile devices. *outputStride* specifies the output stride of the *PoseNet* model. The parameters 8, 16, 32 are supported for the *MobileNetV1* architecture, and we defined the intermediate value 16. *InputResolution* is the parameter to define input image dimensions, which is based on the dimensions of the device display. *multiplier* is a float multiplier to define the number of channels for convolution operations. We defined the 0.50 multiplier as recommended for mobile devices by the documentation [60]. The final result is a data set returned by the net.estimatePoseOnImage() function, which is an object of type *Pose* that contains: an overall confidence score for the estimation, 17 (seventeen) key-points of the body with their coordinates, and a confidence score for each identified point. Coordinates are used to visually display green points and lines on the image.

From this implementation, an initial test was carried out by taking photographs of a participant with the developed prototype. For the photographic record, the assessor positioned himself 3 m in front of the participant and photographed her in the front view. A popular smartphone in Brazil was used for testing purposes, which has the following specifications: Android 7.0, 1.1 GHz octa-core processor, 1.8 GB RAM, and 13MP camera. During photographic recording and data processing, the device was connected to the Internet via a wireless network. Fig. 2 presents the ASPs of the participant identified by the mobile application. Fig. 3 shows the lines drawn by the mobile application from the

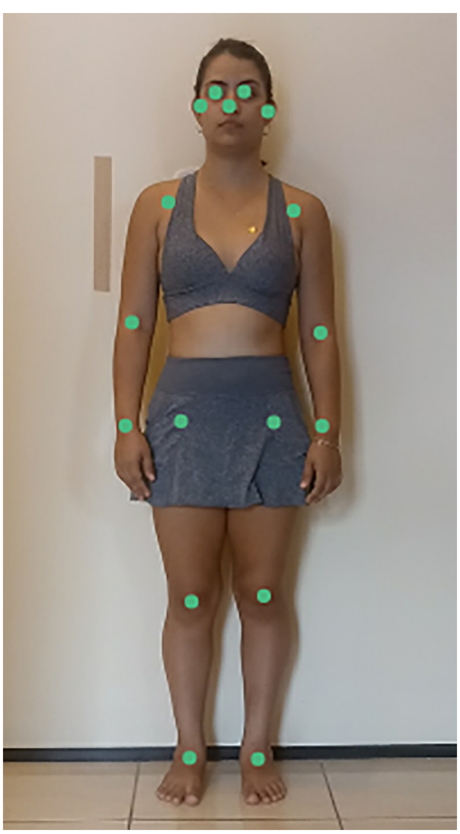

Fig. 2. ASPs identified by the mobile application prototype.

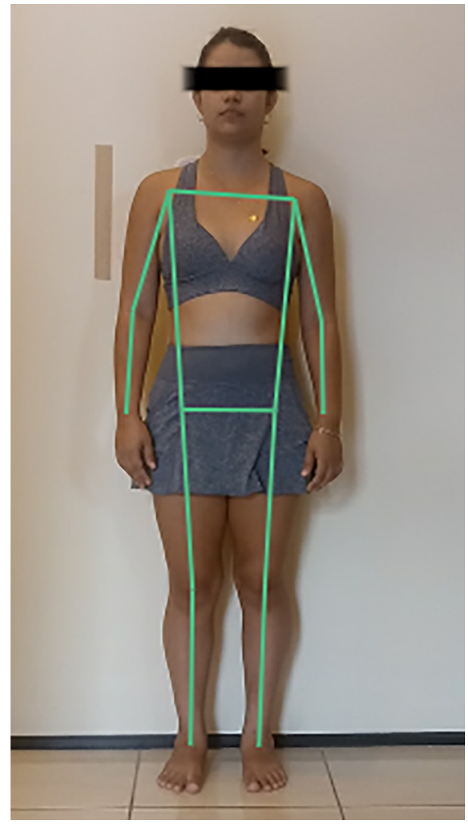

Fig. 3. Lines drawn by the mobile application prototype from the identified ASPs.

identified ASPs. Point identification and line drawing are already resources provided by the *PoseNet*. As we can see, *PoseNet* enables to identify 17 (seventeen) ASPs defined as key-points. In addition, we see lines connecting these points and, from them, we believe it is possible to calculate the real distance between them (i.e., anthropometry) by considering reference points.

To find out if the identified points in the photograph are the ASPs learned by the ML algorithm, *PoseNet* framework has a feature to calculate the confidence score of the point identification process. That is, it enables to verify whether the points identified on the photograph actually correspond to the ASPs. The marking of the points is conditioned by the level of accuracy in identifying these points according to a threshold predefined by the developer. In a case when the accuracy is low (i.e., lower than the predefined threshold), the points are not precisely identified and may not be marked in the photo. In this case, photograph should be discarded with a new registration required. In our developed prototype, we predefined the threshold 0.75. Table 1 presents the ASPs identified with the mobile application prototype and the confidence scores calculated after the photographic record.

Once ASPs and distance between them are identified, we envision the possibility of calculating angular measurements at the points of intersection between the lines that mark anatomical segments. These angular measurements may vary according to the difference in bilateral position at ASPs. It is expected that the ASPs, identified bilaterally, are at the same axis of the body, making it possible to draw a line between them. When there is a misalignment between these points, angular measurements may vary and indicate the presence of postural deviations. With the application allowing to calculate these angular values, it will also be possible to use them for assessments of ROM and posture whose values are given in degrees.

Table 1
Confidence score for each anatomical point identified by the mobile application prototype.

ASP	Confidence score
Nose	1.0
Left eye	1.0
Right eye	1.0
Left ear	0.92
Right ear	0.77
Left shoulder	1.0
Right shoulder	1.0
Left elbow	0.99
Rigth elbow	0.99
Left wrist	0.98
Right wrist	1.0
Left hip	0.99
Right hip	0.98
Left knee	0.99
Right knee	0.99
Left ankle	0.93
Right ankle	0.97

Discussion and consequences of our hypothesis

Posture and movement are two physical components that influence the quality of a person's health. Active movement is a physical skill inherent to a physiologically healthy human beings directly related to their functional capacity and, therefore, necessary for individual health preservation [61,62]. However, the fact that human beings are able to actively move does not imply that they are healthy, since the quality and quantity of this movement also need to be considered during the physical evaluation [45]. Body posture also influences people's health, especially when postural changes affect the alignment and structural organization of the spine. Postural deviations such as scoliosis, hyperkyphosis and hyperlordosis may indicate, or even trigger other pathological and functional changes [63]. For example, the posture that a person adopted during sleep may indicate changes related to sleep apnea [64] or even carpal tunnel syndrome [65], characterized by pain in the wrist region. Posture is also a physical variable of interest in ergonomic assessments performed to identify environmental factors that may influence onset of postural disorders or to assess the relationship of postural changes and the onset of other musculoskeletal disorders [66].

Since posture and ROM are directly related to individual health, auxiliary methods and tools for objective assessment of these variables have been developed over the years. Systems for Postural (e.g., SAPO) and ROM (e.g., goniometer) assessment are presented as methods of easy handling and good accuracy and, therefore, they would be used more routinely in clinical practice [67]. For example, SAPO assists professionals in performing objective assessments, by providing quantitative data on the alignment, which is presented in degrees, of the bilateral anatomical segments (e.g., horizontal alignment of the head, horizontal alignment of the acromions, anterior superior iliac spines, frontal angle of the right and left limbs, length difference of the lower limbs) [68]. However, it requires that a large number of anatomical points on the patient's body to be previously marked with reflective markers. SAPO protocol for marking ASPs suggests to define 27 points from the anterior view, 42 points from the posterior view, and 31 points from the right or left side view. The process of marking these points is time consuming, because health professionals require to prepare patients properly following the protocol, hence leaving them more time exposed to the assessment procedure.

Goniometry, which is traditionally performed using a universal goniometer, is considered a reliable method to assess ROM. It is a kind of ruler with a 360-degree axis that allows professionals to measure the degree of angular displacement of the segment around joints [69]. Although the universal goniometer is a practical, inexpensive and reliable instrument, much remains to be done to assist in the ROM assessment. The displacement of the goniometer axis during the measurement and, consequently, the time spent to take goniometric measurements are negative factors that can compromise the assessment result. In addition, new evidence reveals that goniometer and visual estimation methods may be inaccurate for measuring some angles, suggesting that they should not be used if an accurate assessment is required [70].

These methods and instruments traditionally are used to help in the evaluative processes, however, posture and ROM assessment have been increasingly optimized with the use of mobile applications or sensors embedded in smartphones [71,72], ML algorithms [73] and CV models [18,74]. Computer systems (e.g., SAPO), used in posture assessments require identified ASPs and the distance between them, which are used as reference points for assessment. However, existing assessment systems still require this demarcation to be carried out manually. Recently, an mobile solution named PostureScreen has made a breakthrough in this process, allowing ASPs to be marked directly on the device screen. Despite this advance, the marking process is still performed manually and depends on the interference of the health professional.

Mobile applications have also been applied to assess ROM, as presented by Behnoush et al. [75] who used a system based on the smartphone inclinometer to assess elbow movement, which showed high reliability (ICC $>$ 95) in relation to the universal goniometer. However, mobile systems identified in the literature are based on inclinometers and accelerometers, which requires the smartphone to be positioned on the center of the joint and held by the professional, a procedure that may produce the same bias as that found with the universal goniometer (i.e., there may be the displacement of the smartphone from the location initially positioned). Photographs have also been used to assess ROM, but the identification of ASPs and the processing and calculation of ROM are performed by other software solutions (e.g., Adobe Photoshop [76]), therefore the complete process is not automatic.

The hypothesis presented in this paper argues that it is possible to develop a mobile solution to assess the posture and ROM from the automatic identification of ASPs and the distance between them, differing from traditional systems that require manual marking. This automation can be provided from the use of CV models that are associated with ML algorithms already available in different solutions and able to be embedded into smartphone mobile applications. For example, TensorFlow *library* in combination with the *PoseNet* package, which we tested in the initial evaluation of this hypothesis, provide a framework that enables the estimation of human position from the identification of ASPs. Another possible solution to be investigated to avoid manual marking of ASPs *is PyTorch* framework, which also has a mobile version [77] and provides CV models [78] ready to be extended.

The development and validation of a mobile solution proposed in this hypothesis would imply another change in the assessment process, since it would not be necessary the patient to wear a small amount of clothing (i.e., bikinis, swimwear). This aspect is advantageous for the patient, as the body is less exposed, and for the health professional, who will spend less time to perform the assessment process. Another advantage that can be pointed out is that the examiner does not need to perform palpation repeatedly on the patient, a procedure that can often spend a lot of time, depending on the examiner's experience. Moreover, another point to note is that, with palpation being performed less frequently, it reduces the chance of the patient complaining of discomfort related to the manual touch.

From the identification data of the ASPs, it will be possible to assess posture and ROM using a mobile application to perform measurements of postural deviations and goniometry. As a consequence, it will be required to assess the accuracy of this system as an assessment method of human posture and ROM in order to guarantee to professionals that values found in the assessment are reliable. For this, it will be necessary to compare measurements made between a mobile system and well-known systems for postural (e.g., SAPO, DIPA, PostureScreen) and ROM (e.g., goniometer) assessments. A mobile system for postural and ROM assessment based on the automatic identification of ASPs would minimize biases produced by traditional methods. For example, when using the universal goniometer, professionals normally use both hands to stabilize the goniometer at the correct positioning, however, it is difficult to keep the limbs and goniometer stability while the patient moves the body segment to be assessed, which may cause reading errors [75]. This process can also be optimized by the automated system that we are showing in the hypothesis, which could be even more improved by integrating sensor technologies (e.g., gyroscope and accelerometer) already used by sensor-based mobile systems for human posture analysis [79,72,80].

In addition to the consequences and advantages already mentioned, we must note that all discussed physical assessment features will be available on a mobile device. This means that the health professional will carry the assessment anywhere and anytime. For professionals, this will lead to a reduction in expenses, since they will not need to buy and carry materials such as tripods to support cameras, plumb lines and reflective markers.

It is necessary to highlight that a mobile system that can be developed and proposed from this hypothesis does not envisage replacing the role of specialized health professionals. We believe that such a mobile application will contribute and facilitate the clinical interpretation of professionals.

Author contributions

Rayele Moreira, Ariel Teles and Renan Fialho designed and developed the hypothesis. They wrote the manuscript. Samila Sousa Vasconcelos, Itamara Carvalho de Sá, Thalyta Cibele Passos dos Santos, Victor Hugo Bastos, Francisco Silva and Silmar Teixeira, helped with editing, reviewing, scientific inputs, and final presentation.

Ethical approval

The ethics committee of the Federal University of Piauí approved all procedures for the study (number 2.927.518). Informed consent was obtained from the study participant.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] Zaidi Z. Body asymmetries: incidence, etiology and clinical implications. Aust J Basic Appl Sci 2011;5:2157–91.
[2] Pereira L, Botelho A, Fachin-Martins E. Relationships between body symmetry during weight-bearing and functional reach among chronic hemiparetic patients. Rev Brasil Fisioterapia 2010;14:229–66. https://doi.org/10.1590/S1413-35552010000300009.
[3] Iosa M, Paradisi F, Brunelli S, Delussu A, Pellegrini R, Zenardi D, et al. Assessment of gait stability, harmony, and symmetry in subjects with lower-limb amputation evaluated by trunk accelerations. J Rehabil Res Dev 2014;51:623–34. https://doi.org/10.1682/JRRD.2013.07.0162.
[4] M. Eliks, O. Wioleta, P. Lisínski, P. Koczewski, Does structural leg-length discrepancy affect postural control? preliminary study, BMC Musculoskeletal Disorders 18. doi:10.1186/s12891-017-1707-x.
[5] Sabharwal S, Kumar A. Methods for assessing leg length discrepancy. Clin Orthop Relat Res 2008;466(12):2910–22. https://doi.org/10.1007/s11999-008-0524-9.
[6] Kutilek P, Viteckova S, Svoboda Z, Smrcka P. Kinematic quantification of gait asymmetry in patients with peroneal nerve palsy based on bilateral cyclograms. J Musculoskelet Neuronal Interact 2013;13(2):244–50.
[7] Thonnard J-L, Penta M. Functional assessment in physiotherapy. A literature review. Europa medicophysica 2007;43:525–41.
[8] Moncrieff MJ, Livingston LA. Reliability of a digital-photographicgoniometric method for coronal-plane lower limb measurements. J Sport Rehabil 2009;18(2):296–315. https://doi.org/10.1123/jsr.18.2.296.
[9] Singla D, Veqar Z. Methods of postural assessment used for sports persons. J Clin Diagn Res 2014;8(4):LE01–4. https://doi.org/10.7860/JCDR/2014/6836.4266.
[10] Gajdosik RL, Bohannon RW. Clinical measurement of range of motion: review of goniometry emphasizing reliability and validity. Phys Ther 1987;67(12):1867–72. https://doi.org/10.1093/ptj/67.12.1867.
[11] E. M. Porto De Freitas Camelo, D. Matias Uc̆hoa, F. Santos Júnior, T. Brasileiro de Vasconcelos, R. Macena, Use of softwares for posture assessment: Itegrative review, Coluna/ Columna 14 (2015) 230. doi:10.1590/S1808-185120151403139932.
[12] Furlanetto TS, Sedrez JA, Candotti CT, Loss JF. Photogrammetry as a tool for the postural evaluation of the spine: a systematic review. World J Orthopedics 2016;7(2):136–48. https://doi.org/10.5312/wjo.v7.i2.136.
[13] Furlanetto TS, Candotti CT, Comerlato T, Loss JF. Validating a postural evaluation method developed using a digital image-based postural assessment (dipa) software. Comput Methods Programs Biomed 2012;108(1):203–12. https://doi.org/10.1016/j.cmpb.2012.03.012.
[14] Hébert-Losier K, Rahman FA. Reliability of postural measures in elite badminton players using posture pro 8. Physiother Theory Pract 2018;34(6):483–94. https://doi.org/10.1080/09593985.2017.1420117.
[15] Jones A, Sealey R, Crowe M, Gordon S. Concurrent validity and reliability of the simple goniometer iphone app compared with the universal goniometer. Physiother Theory Pract 2014;30(7):512–6. https://doi.org/10.3109/09593985.2014.900835.
[16] Reina N, Cognault J, Ollivier M, Dagneaux L, Gauci M-O, Pailhé R. The cjortho app: a mobile clinical and educational tool for orthopedics. Orthopaed Traumatol Surgery Res 2018;104(4):523–7. https://doi.org/10.1016/j.otsr.2018.01.022.
[17] Boland DM, Neufeld EV, Ruddell J, Dolezal BA, Cooper CB. Inter- and intra-rater agreement of static posture analysis using a mobile application. J Phys Ther Sci 2016;28(12):3398–402. https://doi.org/10.1589/jpts.28.3398.
[18] Szucs KA, Brown EVD. Rater reliability and construct validity of a mobile application for posture analysis. J Phys Ther Sci 2018;30(1):31–6. https://doi.org/10.1589/jpts.30.31.
[19] Hopkins BB, Vehrs PR, Fellingham GW, George JD, Hager R, Ridge ST. Validity and reliability of standing posture measurements using a mobile application. J Manipulative Physiol Ther 2019;42(2):132–40. https://doi.org/10.1016/j.jmpt.2019.02.003.
[20] Google, Tensorflow. URL https://www.tensorflow.org/.
[21] Google, Pose estimation - posenet. URL https://www.tensorflow.org/lite/models/pose_estimation/overview.
[22] P. Hamet, J. Tremblay, Artificial intelligence in medicine, Metabolism 69. doi:10.1016/j.metabol.2017.01.011.
[23] Deo RC. Machine learning in medicine. Circulation 2015;132(20):1920–30. https://doi.org/10.1161/CIRCULATIONAHA.115.001593.
[24] Chen JH, Asch SM. Machine learning and prediction in medicine - beyond the peak of inflated expectations. N Engl J Med 2017;376(26):2507–9. https://doi.org/10.1056/NEJMp1702071.
[25] Ebrahimighahnavieh MA, Luo S, Chiong R. Deep learning to detect alzheimer's disease from neuroimaging: A systematic literature review. Comput Methods Programs Biomed 2020;187:105242https://doi.org/10.1016/j.cmpb.2019.105242.
[26] Lin C-H, Hsu K-C, Johnson KR, Fann YC, Tsai C-H, Sun Y, et al. Evaluation of machine learning methods to stroke outcome prediction using a nationwide disease registry. Comput Methods Programs Biomed 2020;190:105381https://doi.org/10.1016/j.cmpb.2020.105381.
[27] Lee Y, Ragguett R-M, Mansur RB, Boutilier JJ, Rosenblat JD, Trevizol A, et al. Applications of machine learning algorithms to predict therapeutic outcomes in depression: a meta-analysis and systematic review. J Affect Disord 2018;241:519–32. https://doi.org/10.1016/j.jad.2018.08.073.
[28] P. H. Yi, J. Wei, T. K. Kim, H. I. Sair, F. K. Hui, G. D. Hager, J. Fritz, J. K. Oni, Automated detection & classification of knee arthroplasty using deep learning, The Kneedoi:10.1016/j.knee.2019.11.020.
[29] Larson DB, Chen MC, Lungren MP, Halabi SS, Stence N, Langlotz CP. Performance of a deep-learning neural network model in assessing skeletal maturity on pediatric hand radiographs. Radiology 2018;287(1):313–22. https://doi.org/10.1148/radiol.2017170236.
[30] N. Nasrullah, J. Sang, M. S. Alam, M. Mateen, B. Cai, H. Hu, Automated lung nodule detection and classification using deep learning combined with multiple strategies, Sensors 19 (17). doi:10.3390/s19173722.
[31] Bartlett R. Artificial intelligence in sports biomechanics: new dawn or false hope? J Sports Sci Med 2006;5:474–9.
[32] Giles B, Kovalchik S, Reid M. A machine learning approach for automatic detection and classification of changes of direction from player tracking data in professional tennis. J Sports Sci 2020;38(1):106–13. https://doi.org/10.1080/02640414.2019.1684132.
[33] M. Airaksinen, O. R¨as¨anen, E. Iĺen, T. H¨ayrinen, A. Kivi, V. Marchi, A. Gallen, S. Blom, A. Varhe, N. Kaartinen, L. Haataja, S. Vanhatalo, Automatic posture and movement tracking of infants with wearable movement sensors, Scientific Reports 10 (1). doi:10.1038/s41598-019-56862-5.
[34] L. Costa, M. F. Gago, D. Yelshyna, J. Ferreira, H. David Silva, L. Rocha, N. Sousa, E. Bicho, Application of machine learning in postural control kinematics for the diagnosis of alzheimer's disease, Computational Intelligence and Neuroscience doi:10.1155/2016/3891253.
[35] A. Toshev, C. Szegedy, Deeppose: Human pose estimation via deep neural networks, 2014 IEEE Conference on Computer Vision and Pattern Recognition doi:10.1109/cvpr.2014.214.
[36] A. Mathis, P. Mamidanna, K. Cury, T. Abe, V. Murthy, M. Mathis, M. Bethge, Deeplabcut: markerless pose estimation of user-defined body parts with deep learning, Nature Neuroscience 21. doi:10.1038/s41593-018-0209-y.
[37] M. Abadi, P. Barham, J. Chen, Z. Chen, A. Davis, J. Dean, M. Devin, S. Ghemawat, G. Irving, M. Isard, M. Kudlur, J. Levenberg, R. Monga, S. Moore, D. G. Murray, B.

Steiner, P. Tucker, V. Vasudevan, P. Warden, M. Wicke, Y. Yu, X. Zheng, Tensorflow: A system for large-scale machine learning, in: 12th Symposium on Operating Systems Design and Implementation, 2016, pp. 265–283.
[38] W. G. O. for eHealth, mhealth: new horizons for health through mobile technologies: second global survey on ehealth (2011).
[39] Kumar S, Nilsen W, Pavel M, Srivastava M. Mobile health: Revolutionizing healthcare through transdisciplinary research. Computer 2013;46(1):28–35. https://doi.org/10.1109/MC.2012.392.
[40] D. M. Hilty, S. Chan, J. Torous, J. Luo, R. J. Boland, Mobile health, smartphone/device, and apps for psychiatry and medicine: Competencies, training, and faculty development issues, Psychiatric Clinics of North America 42 (3) (2019) 513-534, professional Development for Psychiatrists. doi:10.1016/j.psc.2019.05.007.
[41] J. Doupis, G. Festas, C. Tsilivigos, V. Efthymiou, A. Kokkinos, Smartphone-based technology in diabetes management, Diabetes Therapydoi:10.1007/s13300-020-00768-3.
[42] E. Múrias Lopes, M. d. C. Vilas-Boas, D. Dias, M. J. Rosas, R. Vaz, J. P. Silva Cunha, ihandu: A novel quantitative wrist rigidity evaluation device for deep brain stimulation surgery, Sensors 20 (2). doi:10.3390/s20020331.
[43] K. Tchelet, A. Stark-Inbar, Z. Yekutieli, Pilot study of the encephalog smartphone application for gait analysis, Sensors 19 (23). doi:10.3390/s19235179.
[44] Rawstorn JC, Gant N, Warren I, Doughty RN, Lever N, Poppe KK, et al. Measurement and data transmission validity of a multi-biosensor system for real-time remote exercise monitoring among cardiac patients. JMIR Rehabil Assist Technol 2015;2(1):e2https://doi.org/10.2196/rehab.3633.
[45] P. Lisiński, A. Wareńczak, K. Hejdysz, P. Sip, J. Gośliński, P. Owczarek, J. Jonak, J. Goślińska, Mobile applications in evaluations of knee joint kinematics: A pilot study, Sensors 19 (17). doi:10.3390/s19173675.
[46] Ramkumar PN, Haeberle HS, Ramanathan D, Cantrell WA, Navarro SM, Mont MA, et al. Remote patient monitoring using mobile health for total knee arthroplasty: Validation of a wearable and machine learning–based surveillance platform. J Arthroplasty 2019;34(10):2253–9. https://doi.org/10.1016/j.arth.2019.05.021.
[47] Gogia PP, Braatz JH, Rose SJ, Norton BJ. Reliability and validity of goniometric measurements at the knee. Phys Ther 1987;67(2):192–5. https://doi.org/10.1093/ptj/67.2.192.
[48] Milani P, Coccetta CA, Rabini A, Sciarra T, Massazza G, Ferriero G. Mobile smartphone applications for body position measurement in rehabilitation: a review of goniometric tools. PM&R 2014;6(11):1038–43. https://doi.org/10.1016/j.pmrj.2014.05.003.
[49] Bucke J, Spencer S, Fawcett L, Sonvico L, Rushton A, Heneghan NR. Validity of the digital inclinometer and iphone when measuring thoracic spine rotation. J Athletic Train 2017;52(9):820–5. https://doi.org/10.4085/1062-6050-52.6.05.
[50] Zinchuk V, Grossenbacher-Zinchuk O. Machine learning for analysis of microscopy images: a practical guide. Curr Protocols Cell Biol 2020;86(1):e101https://doi.org/10.1002/cpcb.101.
[51] X. Chen, A. Yuille, Articulated pose estimation by a graphical model with image dependent pairwise relations, in: Proceedings of the 27th International Conference on Neural Information Processing Systems - Volume 1, NIPS'14, MIT Press, Cambridge, MA, USA, 2014, p. 1736–1744.
[52] Google, Posenet - camera feed demo. URL https://storage.googleapis.com/tfjs-models/demos/posenet/camera.html.
[53] Google, Mediapipe. URL https://github.com/google/mediapipe/blob/master/README.md.
[54] Google, Tensorflow lite. URL https://www.tensorflow.org/lite.
[55] I. Bratko, Machine learning: Between accuracy and interpretability, in: G. Della Riccia, H.-J. Lenz, R. Kruse (Eds.), Learning, Networks and Statistics, Springer Vienna, Vienna, 1997, pp. 163–177.
[56] Powers D. Evaluation: grom precision, recall and f-measure to roc, informedness, markedness & correlation. J Mach Learn Technol 2011;2(1):37–63. https://doi.org/10.9735/2229-3981.
[57] Voulodimos A, Doulamis N, Doulamis A, Protopapadakis E. Deep learning for computer vision: a brief review. Comput Intell Neurosci 2018;2018:1–13. https://doi.org/10.1155/2018/7068349.
[58] Clark RA, Mentiplay BF, Hough E, Pua YH. Three-dimensional cameras and skeleton pose tracking for physical function assessment: a review of uses, validity, current developments and kinect alternatives. Gait & Posture 2019;68:193–200. https://doi.org/10.1016/j.gaitpost.2018.11.029.
[59] I. Framework, Ionic - cross-platform mobile app development. URL https://ionicframework.com/.
[60] Google, Pose detection in the browser: Posenet model. URL https://github.com/tensorflow/tfjs-models/tree/master/posenet.
[61] Lindberg P, Schmitz C, Forssberg H, Engardt M, Borg J. Effects of passive-active movement training on upper limb motor function and cortical activation in chronic patients with stroke: a pilot study. J Rehabil Med 2004;36:117–23. https://doi.org/10.1080/16501970410023434.
[62] Ranzi C, Barroso BF, Pegoraro DR, Sachetti A, Rockenbach CWF, Calegari L. Effects of exercises on pain and functional capacity in hospitalized cancer patients. Braz J Pain – BrJP 2019;2:255–9. https://doi.org/10.5935/2595-0118.20190045.
[63] Liu S, Yin Y, Ostadabbas S. In-bed pose estimation: deep learning with shallow dataset. IEEE J Transl Eng Health Med 2019;7:1–12. https://doi.org/10.1109/JTEHM.2019.2892970.
[64] Lee CH, Kim DK, Kim SY, Rhee C-S, Won T-B. Changes in site of obstruction in obstructive sleep apnea patients according to sleep position: a dise study. Laryngoscope 2015;125(1):248–54. https://doi.org/10.1002/lary.24825.
[65] McCabe SJ, Gupta A, Tate DE, Myers J. Preferred sleep position on the side is associated with carpal tunnel syndrome. HAND 2011;6(2):132–7. https://doi.org/10.1007/s11552-010-9308-2.
[66] Iacob SM, Chisnoiu AM, Lascu LM, Berar AM, Studnicska D, Fluerasu MI. Is posturescreen R mobile app an accurate tool for dentists to evaluate the correlation between malocclusion and posture? CRANIO R 2018:1–7. https://doi.org/10.1080/08869634.2018.1512197.
[67] Ferreira EAG, Duarte M, Maldonado EP, Burke TN, Marques AP. Postural assessment software (PAS/SAPO): validation and reliabiliy. Clinics 2010;65:675–81. https://doi.org/10.1590/S1807-59322010000700005.
[68] D. M., F. E.A., M. E.P., F. A.Z., Documentação sobre o sapo - software para avaliação postural (sapo documentation - written in portuguese language). URL http://pesquisa.ufabc.edu.br/bmclab/sapo2/SAPOdoc.pdf.
[69] Carvalho RMFD, Mazzer N, Barbieri CH. Analysis of the reliability and reproducibility of goniometry compared to hand photogrammetry. Acta Ortopédica Bras 2012;20:139–49. https://doi.org/10.1590/S1413-78522012000300003.
[70] G. E. Hancock, T. Hepworth, K. Wembridge, Accuracy and reliability of knee goniometry methods, Journal of Experimental Orthopaedics 5 (1). doi:10.1186/s40634-018-0161-5.
[71] Yang L, Grooten WJ, Forsman M. An iphone application for upper arm posture and movement measurements. Appl Ergon 2017;65:492–500. https://doi.org/10.1016/j.apergo.2017.02.012.
[72] Nath ND, Akhavian R, Behzadan AH. Ergonomic analysis of construction worker's body postures using wearable mobile sensors. Appl Ergon 2017;62:107–17. https://doi.org/10.1016/j.apergo.2017.02.007.
[73] S. Moccia, L. Migliorelli, V. Carnielli, E. Frontoni, Preterm infants' pose estimation with spatio-temporal features, IEEE Transactions on Biomedical Engineeringdoi:10.1109/TBME.2019.2961448.
[74] Kunkle WA, Madden M, Potts S, Fogelson J, Hershman S. Validity of a smartphone protractor to measure sagittal parameters in adult spinal deformity. Spine J 2017;17(10):1559–64. https://doi.org/10.1016/j.spinee.2017.06.014.
[75] Behnoush B, Tavakoli N, Bazmi E, Fard FN, Hossein M, Shahi P, et al. Smartphone and universal goniometer for measurement of elbow joint motions: a comparative study. Asian J Sports Med 2016;7(2):e30668https://doi.org/10.5812/asjsm.30668.
[76] Meislin MA, Wagner ER, Shin AY. A comparison of elbow range of motion measurements: smartphone-based digital photography versus goniometric measurements. J Hand Surgery 2016;41(4):510–5. https://doi.org/10.1016/j.jhsa.2016.01.006.
[77] PyTorch, Pytorch mobile framework. URL https://pytorch.org/mobile/home/.
[78] PyTorch, Pytorch models. URL https://pytorch.org/hub/.
[79] Y. Wang, H. Zhou, Z. Yang, O. W. Samuel, W. Liu, Y. Cao, G. Li, An intelligent wearable device for human's cervical vertebra posture monitoring, in: 2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), 2018, pp. 3280–3283. doi:10.1109/EMBC.2018.8512896.
[80] P. Carvalho, S. Queirós, A. Moreira, J. H. Brito, F. Veloso, M. Terroso, N. F. Rodrigues, J. L. Vilaça, Instrumented vest for postural reeducation, in: IEEE 5th International Conference on Serious Games and Applications for Health (SeGAH), 2017, pp. 1–8. doi:10.1109/SeGAH.2017.7939300.