Towards Accurate Computer Vision-Based Marker Less Human Joint Localization for Rehabilitation Purposes

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Abstract

In this paper we present a computer vision (CV) based prototype application for knee range of motion analysis. The prototype is built on top of an existing CV pose estimation technique, requiring only one web camera. The aim was to investigate whether it can provide adequate measurement accuracy for rehabilitation purposes. Pilot testing were used to compare the accuracy of the prototype with universal goniometer when measuring range of motion of the knee joint. Our research indicates that sufficient accuracy for range of motion analysis of the knee can potentially be achieved in standing and lying positions by extending the underlying training dataset.

Keywords: computer vision, DensePose, marker less, telerehabilitation

1 INTRODUCTION

The COVID- 19 pandemic has forced health care organizations to implement telerehabilitation (TR) as a part of health professionals' daily practice [1]. TR provides the possibility for clients to receive therapy without physically visiting a clinic or hospital. TR has also supported social isolation politics to reduce the spread of COVID-19 [1][2]. Providing easily and equally achieved TR services is a challenge due to the aging population and the concentration of healthcare services [3]. TR can be a way of improving availability of rehabilitation, and is defined as rehabilitation services that is delivered to clients through information and communication technologies (ICT) [4].

TR can involve direct online communication with a health professional, so the client and the health professional are physically at different locations, but it can also mean a technology used in health care that provides automatic feedback and support for the client [5]. Technology that can be used in TR include e.g. telephone, smartphone, computer, tablet, activity trackers, computer vision (CV), artificial intelligence (AI), virtual reality (VR) or robotics [6].

A promising and new way of implementing automatic real-time telerehabilitation services is through CV as the only technical equipment needed is one or more cameras and a computing device, such as laptop, tablet or smartphone. Tracking and analysis of human motions using CV has been an intensive research topic already for decades [7].

Traditional CV based motion analysis uses marker-based approaches, involving installation of dots or other reflective material on key points of the body, such as knee, ankle or shoulder joints. This limitation makes routine use of motion analysis systems impractical, as they require significant technical preparations prior to rehabilitation performance. Three-dimensional (3D) CV systems, such as Vicon, have been used as golden standard in the field of CV [8], however, these include advanced and precisely calibrated equipment and are thus too expensive for home use.

The potential for providing cost-effective and easy-to-use solutions for home environments, marker-less CV solutions for rehabilitations applications have been of interest in the field of TR [9]. Recently, a comparison of marker-less vs. marker-based solutions for Gait analysis through a proof of concept study has been presented in [10]. The authors propose a multi RGB camera neural network based system for detecting and localizing key points of the human body.

In [11] a "semi-marker-less" system is proposed for knee angle measurement during lower limb rehabilitation. The solution is designed for home environments and requires only a single camera. Though, it requires the placement of three physical markers to be able to accurately localize the key joints. The system has shown promising performance results on a robotic arm.

A mobile application, based on computer vision, enabling the automatic identification of anatomical landmarks for recognition of body alignment angles is proposed in [12]. This application, known as NLMeasurer, automatically detects 17 anatomical landmarks from an image consisting of a frontal view of human body. The landmarks can be detected both with and without physical markers attached to the body. Based on these anatomical landmarks

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NLMeasurer can assess the posture. Results from experiments indicate that NLMeasurer provides a valid solution for postural analysis from a frontal view when markers are used. However, when physical markers were not used, the measurements were not fully reliable.

In this paper, we propose a novel CV-based knee angle measurement prototype application for rehabilitation purposes. The prototype only requires a single off-the-shelf web camera and no physical markers. The CV prototype has been developed and critically evaluated within an interdisciplinary research team, including experts from the field of physiotherapy and information technology. As a guideline for the development process the Centre for eHealth Research Roadmap (CeHRes) was used [13].

The rest of the paper is structured as follows: An overview of the technical features of the CV prototype is presented in Section 2. The knee angle measurement performance is critically evaluated in Section 3. Future steps in the development process, with the purpose of extending and improving the accuracy of the measurement capabilities of the CV prototype, are discussed in Section 4. Finally, some concluding remarks are presented in Section 5.

2 COMPUTER VISION BASED KNEE ANGLE MEASUREMENT PROTOTYPE

A prototype application was developed for answering the following research question: Can existing CV-based marker-less human pose estimation techniques, based on a single camera, provide adequate joint localization accuracy for rehabilitation purposes? The technical choices and decisions made for the development are, thus, supported by a systematic review of existing 2D marker-less pose estimation systems [9].

Dense human pose estimation in the wild (DensePose) [15] is a promising technique, in terms of joint localization accuracy. DensePose uses a Region-based Convolutional Neural Nework (R-CNN), based on the Mask R-CNN framework proposed in [14], for mapping all pixels of an RGB image, associated with a human, to the 3D surface of the human body. Based on these 2D to 3D mappings, known as dense correspondences, it then estimates the pose of that person. DensePose is trained on a large-scale ground-truth dataset, called DensePose-COCO [15], with 2D image to 3D surface correspondences manually annotated on 50 000 images. DensePose takes a single image as input and produces, in addition to the dense correspondences, an output image marked with the 2D coordinates of key points of the human body, including ankle, knee, hip, wrist, elbow and shoulder joints (figure 1).

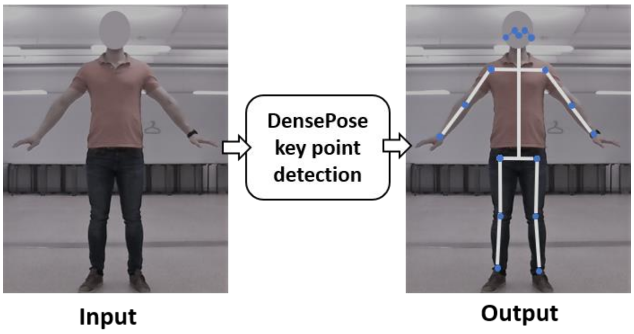
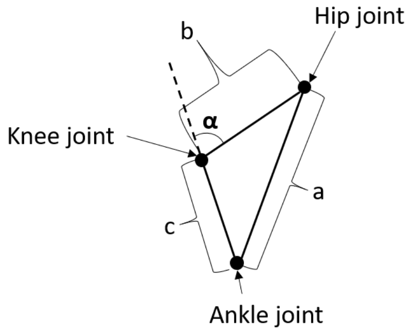


Figure 1. The key point detection feature of DensePose

The key point detection feature of DensePose has been reused in the CV prototype where 2D coordinates of the hip, knee and angle joints are captured for each frame of the input video stream produced by a standard web camera. The knee angle is then calculated applying the law of cosines as shown in figure 2.



$$\alpha = 180 - \text{acos}\left(\frac{a^2+b^2+c^2}{-2ac}\right)$$

α = knee angle
a = distance between ankle and hip joint
b = distance between knee and hip joint
c = distance between knee and ankle joint

Figure 2. The knee angle measurement procedure of the CV prototype

The knee angle measurement procedure is performed for each frame and the CV prototype includes a save button allowing the user to save the knee angle to a log file at any given time. A screen shot of the output of the CV prototype when measuring the knee angle in a stand-up position is shown in figure 3.

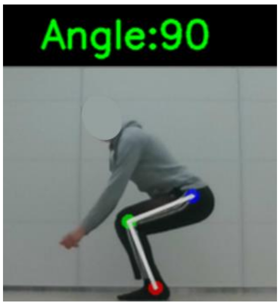


Figure 3. The CV prototype measuring the knee angle of a client in a stand-up position

The CV prototype can be executed on a PC computer equipped with a standard web camera. For the time being, however, it requires a CUDA-enabled NVIDIA GPU. A workaround for this limitation is a distributed approach where the key point detection functionality is executed on a cloud instance and only the user interface is executed locally on the PC, tablet, or smartphone. This will, however, be prioritized in a later stage of our research project.

3 PERFORMANCE EVALUATION

For evaluating the accuracy of the CV prototype, pilot testing was applied to compare the CV prototype with universal goniometer (UG) when measuring subjects' range of motion in the knee joint. In clinical work, physiotherapists typically use UG to measure their clients' joint angles for clinical decision-making and to follow up the rehabilitation process. Goniometric joint angle measurement values can vary up to 5° from the actual angle [16]. This typically happens if the physiotherapist has improper placement of its fulcrum over the center of rotation of the joint or wrong anatomic structures [17].

In our pilot tests, healthy working-age female and male subjects (N = 30) were selected from among the Arcada University of Applied Sciences staff and students. Subjects who suffered from pain or other symptoms in the lower limbs during the preceding 3 months were excluded. Before the pilot test, subjects were provided with written informed consent and a standard written protocol was used when the joint angle measurements were performed. The pilot tests were approved research permission from Arcada University of Applied Sciences, in April 2021.

Knee angle measurement tests were performed on subjects in two different positions, i.e. standing up and lying down. When the subject was in standing position the knees were bent to maximum (deep squat) and when the subject was lying down the knee closest to the camera was bent in a randomized angle. If there was a technical issue with the CV prototype, the result was excluded. Technical issues emerged occasionally when subjects where in lying position with one leg strait and the other leg bent. In this case, the CV prototype sometimes confused the right leg with the left leg and thus produced erroneous values. An example of this problem is shown in figure 4, where the intention of the CV prototype is to measure the knee angle of the left leg, but as the knee joint of the left leg is confused with the right leg, the measurement result is incorrect.

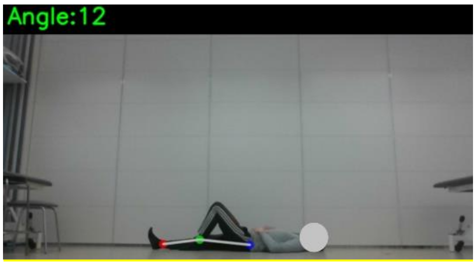


Figure 4. Example where the CV prototype confuses the knee joint of the left leg with the right leg and hence provides an erroneous measurement result

3.1 Performance results

The pilot test included 15 women (mean age 22.6 y) and 15 men (mean age 25.7 y). There was no difference (p=0.2) between genders in mean body-mass index (kg/m2; male mean 23.8, standard deviation (SD) 2.5 vs female mean 22.6, SD 2.3).

The measurement accuracy of the CV prototype was validated by calculating the mean difference between all CV prototype and UG measurement values. When the subjects was in standing position (N=30) and in lying (N=25) the mean difference between UG and CV based knee angle measurements was 3.4°. The variation of the UG and CV measurements values in standing position lied between -6.9 and 13.7 (95% CI) and in lying position between -17.4 and 24.2 (95% CI) from the mean. More detailed results are presented in figure 5 and 6.

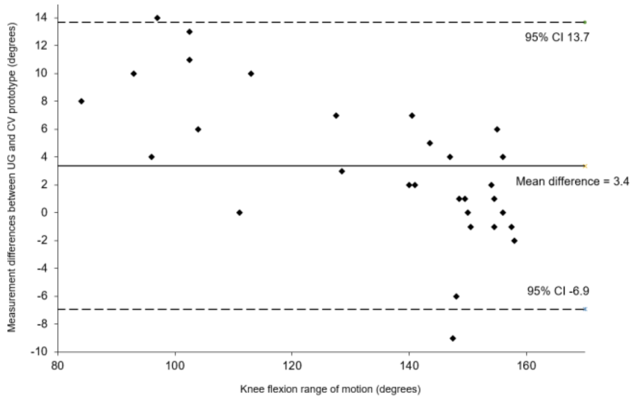


Figure 5. Bland-Altman plots showing the individual measurement differences and the mean difference between CV prototype and UG knee angle measurements in standing position with maximum knee bending. The X-axis denotes the knee bending angle. The Y-axis denotes the measurement differences in degrees between the two methods.

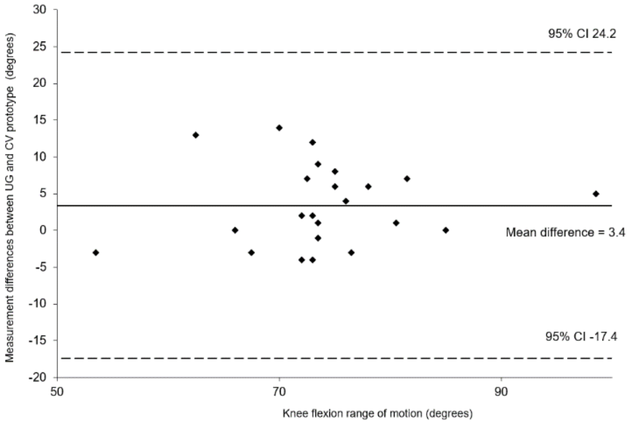


Figure 6. Bland-Altman plots showing the individual measurement differences and the mean difference between CV prototype and UG knee angle measurements for random knee angles when the subject is in lying position. The X-axis denotes the knee bending angle. The Y-axis denotes the measurement differences in degrees between the two methods.

4 DISCUSSION AND FUTURE RESEARCH

A mean difference of 3.4° in the measurement values between the CV prototype and UG can be considered as an acceptable result given UG joint angle measurements as such can vary up to ± 5° in clinical use [16]. However, despite an acceptable mean difference, the variation was still occasionally high.

A possible reason for the variation between the UG and CV measurements is that UG measurements are not exact and CV prototype measurements, on the other hand, were occasionally inconsistent. The main reason for the inconsistency of measurements with the CV prototype is the lack of training data representing people in different positions in the DensePose-COCO dataset. Many of the positions during knee angle measurement are unique, e.g. one leg bent and the other extended. The DensePose-COCO dataset does not include training images with these types of positions and hence the ankle and knee joint of the leg to be measured tend to be confused with the other leg in many occasions leading to erroneous measurement results. The problem is exacerbated by the fact that most of these positions are not of as much interest in typical use, and thus these positions might not be evaluated as rigorously when the original model is trained.

Before the CV prototype is implemented in rehabilitation the accuracy demands has to be resolved, as an incorrect joint angle measurement can affect the clinical decision in rehabilitation. Therefore, as a part of future research, we will investigate how the DensePose-COCO data set could be extended to provide more accurate joint angle measurements and to prevent the mix-up of right and left leg. We will also focus on how our CV prototype application could be extended to also analyze more functional movements used in rehabilitation, such as therapeutic exercises like walking or balance tasks.

5 CONCLUSION

Computer-vision (CV) based marker-less human pose estimation is an attractive technique for telerehabilitation (TR) as it can provide clients with instant feedback on rehabilitation exercises, without the direct involvement of e.g. physiotherapist, and it does not require other hardware than a computing device with a standard web camera. CV based marker-less techniques, however, have not originally been designed for rehabilitation purposes and therefore providing an adequate level of joint localization accuracy, meeting the requirements for rehabilitation purposes, is challenging.

In this paper we have presented a novel CV-based marker-less prototype, based on DensePose, for measuring the angle of the knee joint. Results from pilot testing indicated that an acceptable measurement accuracy is achieved, although there were some errors. Sufficient accuracy for knee range of motion analysis can though potentially be achieved in both standing and lying positions by extending the underlying training dataset.

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7 ACKNOWLEDGEMENT

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