Human Gait Analysis Using OpenPose

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***Abstract*—Gait analysis refers to the scientific study of body movements that are responsible for locomotion in human beings. Gait parameters are known to be reliable indicators of neuromuscular and skeletal health. Gait analysis is used in the design of therapeutic paradigms for stroke and spinal cord injury rehabilitation. In this study, we introduce a marker-less, cost-effective, and user-friendly approach to human gait analysis. We use a simple mobile phone camera and a 2D pose estimation system to obtain important anatomical landmarks. From these landmarks, we calculate the knee flexion/extension angle. Further, we analyze the effects of ambient lighting and the subject's attire on the measured knee angle. We also test the efficacy of our approach by comparing the measured knee angles with a normative gait database. Finally, we compare our results with the knee angle readings obtained using MS Kinect (our previous study).**

***Keywords*—Gait Analysis, OpenPose, Kinect, Neural Networks.**

I. Introduction

The gait cycle comprises of a series of body movements leading to locomotion in human beings. A gait cycle is the duration between successive heel strikes of the same foot. The scientific study of the gait cycle is referred to as gait analysis. One of the earliest and exhaustive works on the human motion was conducted by W.E Weber [1]. He was successful in marking the position of limbs for distinct phases of the gait cycle. The invention of photographic cameras in the early 19^{th} century meant that finer details of human motion could now be recorded and studied. E. Muybridge pioneered the chronophotographic study of human motion analysis [2]. He invented the zoopraxiscope, a device that could playback the captured phases of a gait cycle. The subsequent breakthrough in gait analysis came with the advent of powerful digital computers and image processing techniques. The first video processing system for human gait analysis was developed by R.B. Davis [3]. He used passive reflective markers and image processing algorithms to map human joint motion. A major limitation of reflective markers is that their accuracy of detection is dependent on the ambient lighting conditions [4]. Also, markers placed on the body are susceptible to choppy movements resulting from the sliding of skin over the bones [5]. This introduces noise in the measured gait parameters. With the advancements in integrated circuits and microcontrollers, it became possible to manufacture wearable devices capable of measuring gait metrics [6]. Wearable devices are intrusive and can interfere with the habitual walking of the subject. This is especially true if the devices are heavy, bulky, and connected by wires to some power source. Non-invasive techniques for measurement of gait parameters are also available. They make use of floor sensors, inertial sensors, goniometers, accelerometers and thermal images [7]. These systems are expensive, require extensive calibration, and a controlled environment.

Gait analysis using Microsoft Kinect is a viable non-invasive and cost-effective measurement technique [8]. It makes use of coded infrared grids to develop a 3D depth image of real-world objects. Studies on Kinect have shown that the accuracy of the depth image decreases beyond just 4 cm [9]. Moreover, under bright ambient light, Kinect fails to produce a depth image [9-10]. Also, in our previous study [12], we had shown that knee joint angles measured using Kinect had appreciable accuracy only when the knees were visible, i.e., not covered by clothing. As a result, knee angle measurement using Kinect is difficult for commonly worn Indian attires like a dhoti or saree.

Recent developments in the field of computer vision have attracted much attention from computer scientists owing to its potential in providing elegant solutions to complex image processing problems. Computer vision aims to develop efficient systems that can assist in the understanding of digital images and videos. These techniques are mostly based on Artificial Neural Networks (ANN). ANN's are computing models inspired by the functioning of the human brain. Neural networks consist of nodes interconnected by weighted paths. There exist several types of neural networks depending on their functionality. Convolutional Neural Networks (CNN) are explicitly designed for the analysis and study of digital images [13]. They are employed for a wide variety of applications like image classification, facial recognition, edge detection, scene labeling, semantic segmentation, and human pose estimation [14].

In this work, we suggest an alternative to MS Kinect for gait analysis. We utilize OpenPose, a marker-less 2D human pose estimation system based on CNN to measure knee flexion/extension angles. We test the efficacy of our approach by comparing the obtained knee angle with an open gait database [15]. We also show its superiority over Kinect for knee covering attires worn by the subject.

II. Obtaining Anatomical Landmarks Using OpenPose

Human pose estimation is the process of inferring human poses from a digital image. Pose estimation requires highly accurate detection and identification of human joints. Pose estimation algorithms follow a top-down or a bottom-up approach.

In the top-down approach [16], the first step is to find possible regions of interest from an image. This is followed by the extraction of joints from these regions. Poses are then inferred from the extracted joints. This approach can be

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computationally very expensive as each region is processed independently of one another.

The bottom-up approach [17] begins with the processing of the entire image to obtain possible joint locations. These joints are then connected to generate a pose model. In contrast to the top-down approach, the bottom-up approach is computationally less expensive. But it suffers from the drawback that it can produce faulty pose models due to the erroneous connection of joints.

OpenPose is a bottom-up multi-person pose detection system [18]. It can detect a total of 135 vital body points (no fiducial markers needed) from a digital image. A single CNN is used for both key-point detection and association. The key-points are detected with a score (a numerical value between 0-1). It is a measure of the overall confidence in the key-points estimated. Key-point association is done using part affinity fields (PAF) [19]. They are two-dimensional vector fields that encode the position and orientation of the human limbs.

OpenPose has been trained to produce three distinct pose models. They differ from one another in the number of estimated key-points. a) MPI is the most basic model and can estimate a total of 15 important key-points b) COCO model is a collection of 18 points c) BODY_25 pose consists of 25 points. It can be seen from Fig. 1 that BODY_25 is the most exhaustive pose model. In addition to the key-points estimated by MPI and COCO models, it contains descriptors for the feet and pelvic center. We will be using BODY_25 model in our analysis.

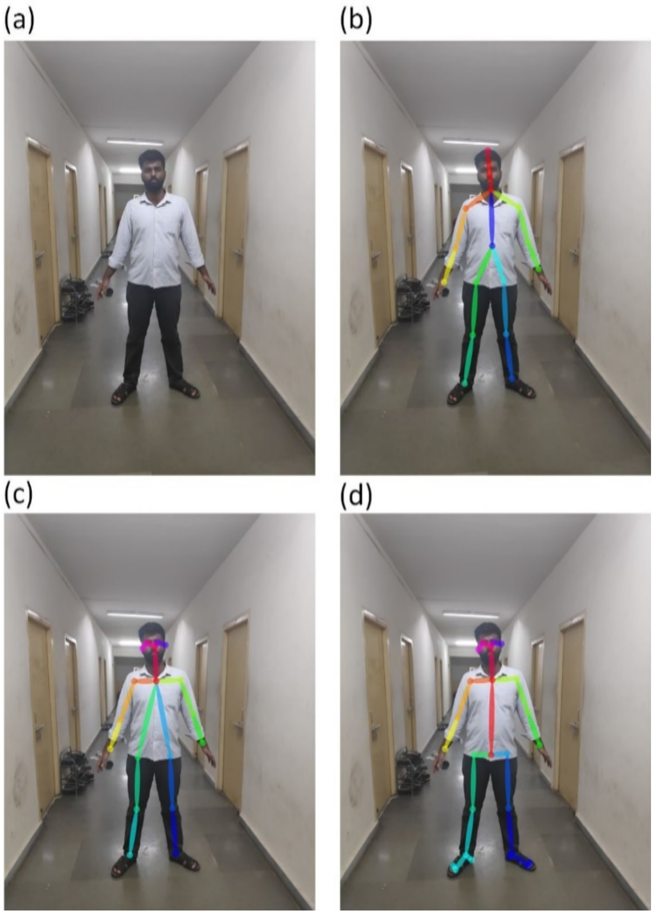

Fig. 1. Illustrations of pose models generate by OpenPose (a) The input image (b) Output pose estimated using MPI model (c) Output pose estimated using COCO model (d) Output pose estimated using BODY_25 model.

Fig. 2. BODY_25 pose estimation results for randomly clicked images.

III. Experimental Setup

The gait cycles were captured using a mobile phone mounted on top of a tripod stand. The phone captures 800 × 600 pixel resolution images at an average rate of 30 frames per second. A total of 10 healthy volunteers participated in this experiment. The average weight and height of the participants were 70.3 kg and 170.5 cm with a standard deviation of 12.3 kg and 8.39 cm respectively. All the participants were dressed in shirts and pants. To study the effect of ambient lighting on knee angle measurement, the subjects were asked to walk parallel to the camera under the following lighting conditions; (1) Dim light at an average radiance of 40 lux and (2) Bright light at an average radiance of 950 lux. Further, to analyze the effects of the knee being covered by clothing, the subjects were made to walk wearing a dhoti (a single piece loose-fitting traditional Indian attire that covers the lower part of the body) under normal lighting (200-300 lux).

Videos of the subjects walking were downloaded onto a computer through a wireless network. For each frame of the video, BODY_25 pose data was generated using OpenPose. From the pose data knee joint angle was calculated.

IV. Calculation Of Knee Angle

The knee angle was calculated using vector dot product. From the hip, knee, and ankle coordinates obtained from the pose data two vectors were constructed. The first vector begins at the hip and ends at the knee while the second one begins at the knee and ends at the ankle. The knee angle (θ) for the frame in Fig. 3 is given by the following equation

$$\theta = \cos^{-1}\left(\frac{\vec{a}\,.\,\vec{b}}{|\vec{a}||\vec{b}|}\right) \tag{1}$$

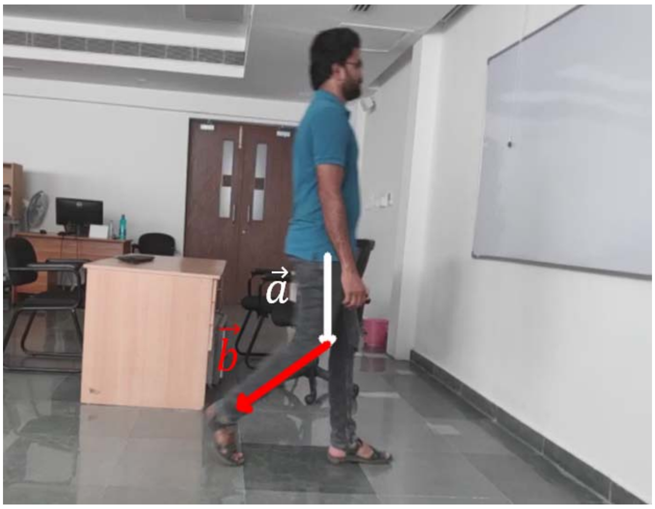

Fig. 3. Knee angle measurement from a video frame.

V. Result

For each of the clothing and lighting conditions, three trials were conducted and the average of the knee angles was calculated.

A. Effects of Ambient Lighting

The percentage errors in the measured knee angles for dim and bright ambient lighting conditions were 16.78% and 13.43% respectively.

TABLE I. Error Due To Variation In Ambient Lighting

	Lighting Condition	
	Dim Lighting	***Bright Lighting***
Error (%)	16.78	13.43
Mean Absolute Deviation	5.85	4.24
Standard Deviation	7.43	5.67

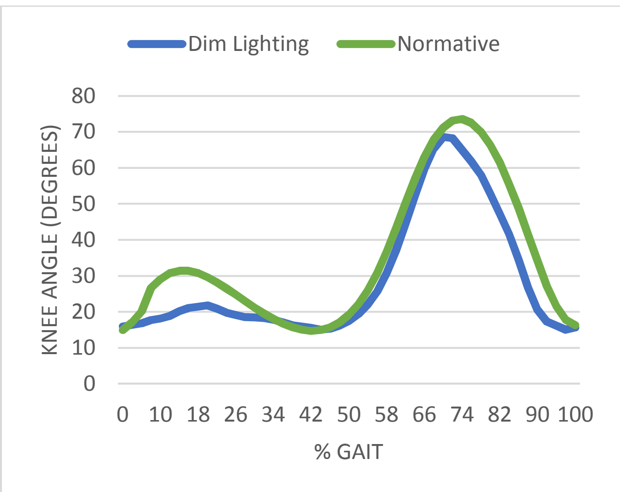

Fig. 4. Average (of 10 subjects) knee flexion/extension angle measured under dim ambient lighting.

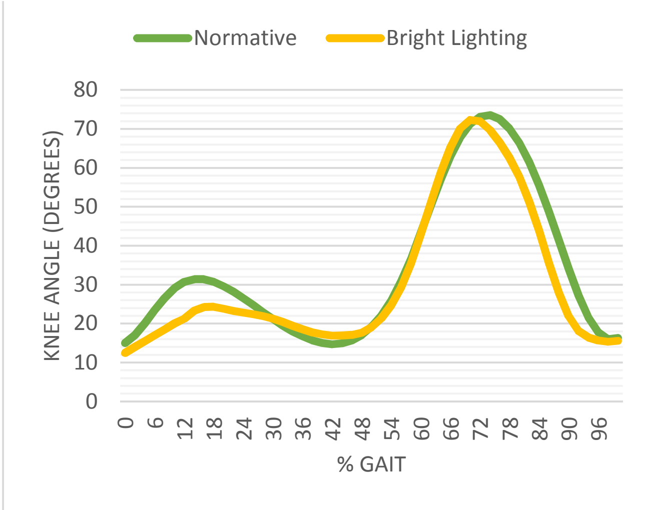

Fig. 5. Average (of 10 subjects) knee flexion/extension angle measured under bright ambient lighting.

B. Effects of Attire

The error in measured knee angle (for normal lighting) with the participants wearing dhoti was 18.29%, and that for pants was 17.8%.

TABLE II. Error Due To Attire

	Attire	
	Dhoti	***Pants***
Error(%)	18.29	17.8
Mean Absolute Deviation	6.40	6.20
Standard Deviation	8.22	7.80

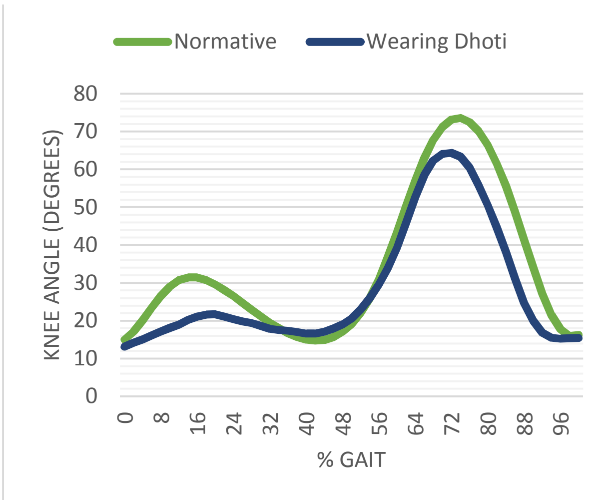

Fig. 6. Average (of 10 subjects) knee flexion/extension angle measured with the subjects wearing dhoti.

VI. Discussion

We observe that there is no appreciable difference (16.78% error under dim lighting and 13.43% error under bright lighting) in the measured knee angle with changes in lighting conditions (radiance variation of approximately 910 lux). We further test the tolerance of OpenPose to extreme ambient lighting by altering the image brightness (Fig. 7a, Fig. 7b, Fig. 7c). These images are then processed to extract

BODY_25 pose data. It is observed that pose and key-point estimation is possible even for extremely whitewashed or darkened images (Fig. 7d, Fig. 7e).

TABLE III. COMPARISON WITH MS KINECT

	Knee Angle Measurement for Dhoti	
	Kinect	***OpenPose***
Error(%)	Could not measure	18.29
Mean Absolute Deviation	Could not measure	6.40
Standard Deviation	Could not measure	8.22

In our previous work [12], we observed that MS Kinect could not detect knee angles for dhotis and other attires that cover the knee. In contrast to Kinect, OpenPose was able to detect knee coordinates with considerable accuracy even when the knees were not visible. A possible reason for this superior performance is due to the CNN employed by OpenPose. The CNN has been designed to estimate key anatomical landmarks/coordinates from images taken under a wide range of conditions. One of the reasons for the failure of Kinect could be due to its depth imaging technique, which can only map objects directly in front of it.

TABLE IV. COMPARISON WITH MS KINECT

	Knee Angle Measurement for Pants	
	Kinect	***OpenPose***
Error(%)	27.28	17.8
Mean Absolute Deviation	6.40	6.20
Standard Deviation	8.22	7.80

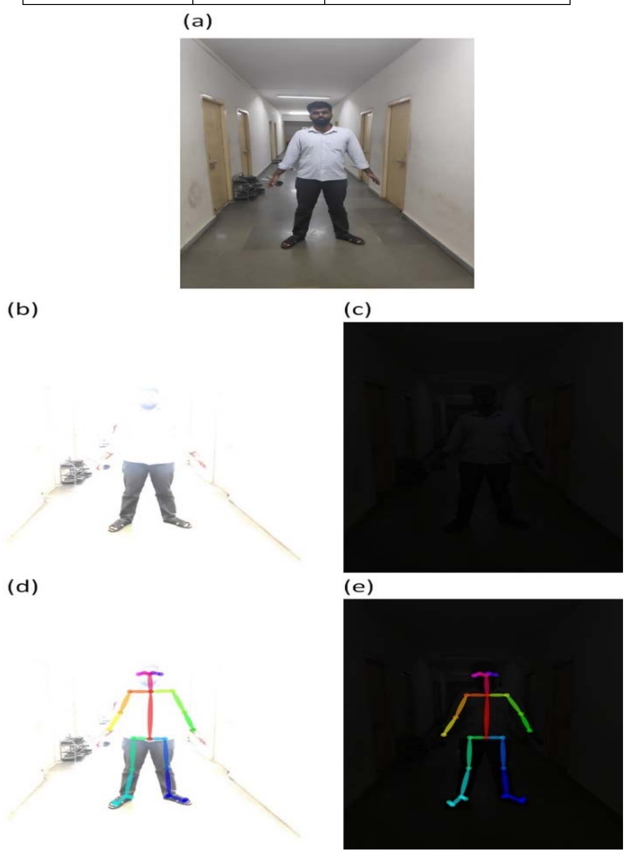

Fig. 7. Body pose estimation for extreme lighting conditions (a) original image (b) whitewashed image (c) darkened image (d) BODY_25 pose estimation for whitewashed image (e) BODY_25 pose estimation for darkened image.

VII. CONCLUSION

We have introduced here a user-friendly, cost-effective and marker-less approach to human gait analysis using OpenPose. We were able to measure knee flexion/extension angles using a simple phone camera and a personal computer. Our approach is tolerant to large variations in ambient lighting. Our results concur well with normative gait database. We also demonstrated that OpenPose based knee angle measurement is superior to Kinect when the subject is wearing day-to-day Indian attires like dhoti (this is also applicable to saree a common dress worn by women).

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