Assessing Knee Joint Movement with AI: Validity and Reliability of Marker-less Motion Capture in the Sagittal Plane

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Summary

Peak knee joint flexion and extension angles were measured by a goniometer and a knee range of motion (ROM) model using a transformer neural network (TNN). The msk.ai TNN model was implemented to predict peak knee joint flexion and extension angles from smartphone videos in home environments. This study compares the validity of this accessible mobile option to goniometer angles measured by a healthcare provider (HCP) in a clinical setting.

Introduction

The measurement of knee joint angles provides valuable information for assessing knee joint function. Universal goniometers (UG) are used by HCP as a cost-effective and accurate measurement tool to assess knee ROM. The use of a UG is dependent on the knowledge and skill of the HCP and access to a clinic. To bypass the need for an HCP or a clinic, a machine learning model called a TNN was trained to assess knee ROM; a TNN is a deep learning model using self-attention for sequence-based tasks like pose estimation [1]. The msk.ai model is a novel application of a TNN, which aims to overcome the need for a clinic or HCP by enabling ROM assessment using smartphone videos. This study assessed the validity of the msk.ai model to estimate peak knee joint flexion and extension angle in a home environment.

Methods

The msk.ai TNN model that was deployed to assess knee joint ROM from smartphone videos was trained using three dimensional (3D) motion capture data and synthesized data. When recording 3D data, participants had three 14mm reflective markers placed on the greater trochanter (GT), lateral epicondyle of the femur (LE), and lateral malleolus (LM) while performing a supine heel slide. All training data underwent image processing to augment the dataset. The size of the training data has further increased in order to mitigate any bias on the training data using the Stable Diffusion model [2]. The training dataset has 193,464 images in total. To test the model, Nineteen subjects (n=19) were recruited for validity and reliability tests to compare UG and TNN. Participants with a history of lower limb surgery or injury that precluded movement were excluded. Knee joint angles were evaluated on all participants using two methods: goniometry by HCP and TNN model. Method (i) followed standard UG procedure with the axis on the LE, stationary arm in line with the GT, and moving arm in line with the fibula toward the LM [3]. Method (ii) utilised a smartphone on a tripod, which ran the camera via bespoke mobile application. The application provided a bounding box and instructions on the screen to guarantee participants were in frame and ensure proper pitch and yaw while filming. For method (ii), participants performed a supine heel slide exercise for three repetitions. All videos were uploaded into cloud storage and processed using the msk.ai TNN model.

Results and Discussion

Results show average differences of 4.27 degrees for peak knee flexion and 3.19 degrees for peak knee extension for model outputs when compared with the UG angles These values had an average confidence of 0.89 for knee joint flexion angles and 0.91 for knee joint extension angles. Root mean squared error (RMSE) between UG measurements and the model were 3.79 degrees for peak knee extension and 4.98 degrees for peak knee flexion.

Conclusions

TNN models show promise in creating an accurate home based assessment tool for knee ROM. The msk.ai algorithm has the potential to reduce the time and effort required to assess knee ROM outside of a clinical setting. Further study and training data are needed to assess the generalizability of such models in care settings.

References

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Table 1: The difference between knee flexion and extension joint angles obtained by UG and the TNN model (msk.ai)

Joint Action	Average UG (°)	SD ±	Average Model (°)	SD ±	Confidence	Mean Difference	RMSE
Flexion	52.31	5.94	55.53	4.53	0.89	4.27	4.98
Extension	174.63	1.92	177.18	2.26	0.91	3.19	3.79