Opportunities for Improving Motor Assessment and Rehabilitation After Stroke by Leveraging Video-Based Pose Estimation

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Opportunities for Improving Motor Assessment and Rehabilitation After Stroke by Leveraging Video-Based Pose Estimation

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Abstract: Stroke is a leading cause of long-term disability in adults in the United States. As the healthcare system moves further into an era of digital medicine and remote monitoring, technology continues to play an increasingly important role in post-stroke care. In this Analysis and Perspective article, opportunities for using human pose estimation—an emerging technology that uses artificial intelligence to track human movement kinematics from simple videos recorded using household devices (e.g., smartphones, tablets)—to improve motor assessment and rehabilitation after stroke are discussed. The focus is on the potential of two key applications: (1) improving access to quantitative, objective motor assessment and (2) advancing telerehabilitation for persons post-stroke.

Key Words: Stroke, Video, Motor, Assessment, Rehabilitation, Physical Therapy, Computer Vision, Pose Estimation

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Approximately 795,000 incidences of stroke occur annually in the United States alone,[1] establishing stroke as a leading cause of long-term disability in adults.[1] Stroke often impairs many aspects of movement,[2] spanning fine motor control of the fingers[3,4] to complex whole-body tasks like walking.[5–7] Rehabilitation is an essential component of post-stroke care because early, effective interventions can lead to significant improvements in motor function.[8]

Like many fields of medicine, rehabilitation continues to accelerate into a digital era. Interest in remote measurement and monitoring of patient function has increased rapidly,[9] and many studies have begun to investigate the feasibility and efficacy of telerehabilitation *vs.* conventional physical therapy[10–12] (Fig. 1). Technological innovations that provide new insight into patient function or advance remote delivery of care will undoubtedly continue to play increasingly important roles in the future of precision (i.e., patient-specific) rehabilitation.[13] Artificial intelligence in particular shows outsized promise not as a replacement for the clinician but as a valuable tool that can provide insight into motor function and inform clinical decision making.[14]

This article looks ahead to discuss promising roles for emerging human pose estimation technology in motor rehabilitation after stroke. Pose estimation is an artificial intelligence technology that uses computer vision to identify and track key features of the human body (e.g., leg joints and fingers) from simple videos that are easily recorded in the home or clinic using common household devices (e.g., smartphones and tablets). This technology offers clear and significant potential for applications in rehabilitation, as it enables quantitative measurement of human movement kinematics in virtually any setting with minimal cost, time investment, and technological requirements. Here, the focus is specifically on applications of pose estimation in post-stroke motor assessment and telerehabilitation.

Effective rehabilitation after stroke requires accurate assessment of a patient's motor abilities and subsequent delivery of an appropriate treatment. There is a need for new methods of post-stroke motor assessment because current methods either are subjective (e.g., clinical scales such as the Fugl-Meyer Assessment[15]), expensive, and inaccessible to most clinicians (e.g., motion capture systems) or provide only limited information about specific, predefined features of movement (e.g., mobile applications, wearables, and gait mats). Reliance on these methods limits our abilities to track rehabilitation outcomes and timelines of post-stroke recovery because measurement is infrequent or data limited. There is a significant role for pose estimation to address all of these limitations by enabling objective, low-cost, comprehensive motor assessment for persons post-stroke.

There are also significant limitations with current approaches to delivery of motor rehabilitation after stroke. Post-stroke rehabilitation is commonly delivered via in-person physical, occupational, and/or speech therapy. This necessitates access to reliable transportation and proximity to a therapy clinic. Furthermore, this model of care assumes that gains achieved in the clinic will translate to real-world activities. Patients in vulnerable and underserved populations are in need of more accessible approaches to rehabilitation therapy,[16–19] creating a clear need to deliver therapy within real-world settings outside of the clinic (e.g., within the home).[20] Pose estimation could eventually facilitate in-home motor rehabilitation to anyone with access to a simple video recording device.

This article is structured into three primary sections. First, there is a brief background on human pose estimation. Second, there is a discussion of applications for pose estimation in

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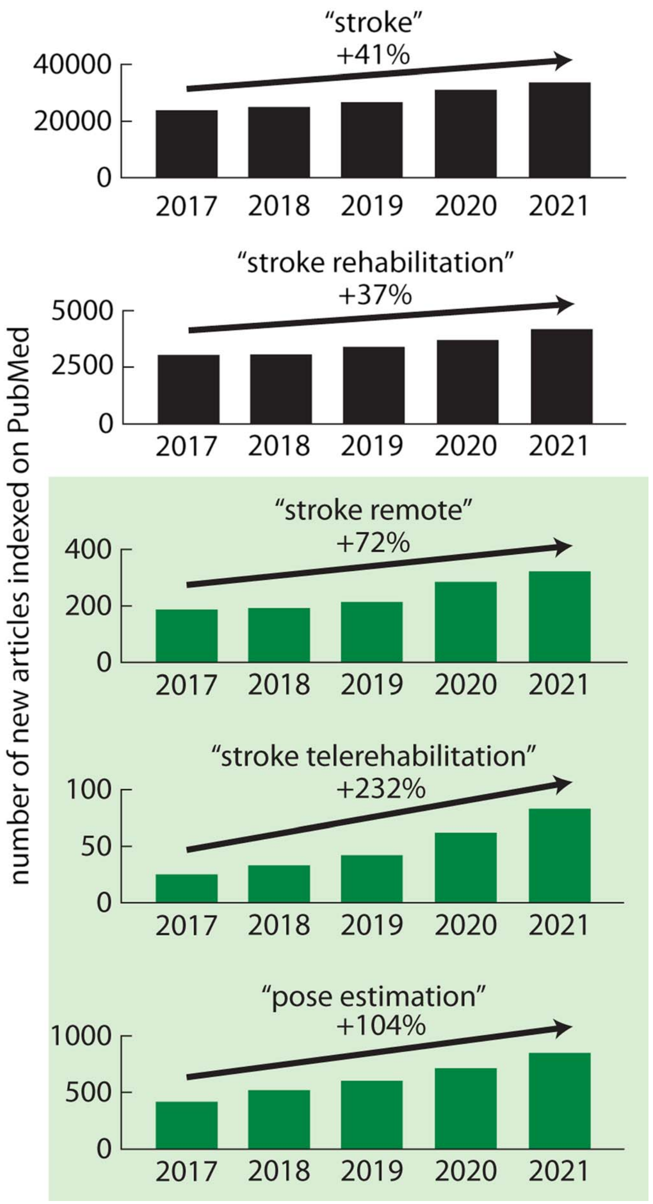

FIGURE 1. The number of new articles indexed on PubMed annually over the past 5 yrs resulting from the following searches (from top to bottom): "stroke," "stroke rehabilitation," "stroke remote," "stroke telerehabilitation," and "pose estimation." Percentages shown above each bar plot indicate growth from 2017 to 2021.

improving quantitative post-stroke motor assessment. Finally, there are proposed applications for leveraging pose estimation to advance telerehabilitation after stroke.

WHAT IS HUMAN POSE ESTIMATION?

Human pose estimation is an artificial intelligence technology that uses computer vision to identify and track key features of the human body from simple videos. A simplified way of thinking about pose estimation is as "motion capture in your pocket," where two- or three-dimensional human movement kinematics can be generated from videos recorded by a common smartphone or tablet device. This technology has rapidly gained traction in data science and neuroscience communities with a wide array of different software options for performing human movement tracking.[21–28] In these fields, it is often used for applications like movement pattern recognition,[29–31] but pose estimation has not yet been used widely in clinical settings or rehabilitation science (with notable limitations of current algorithms reviewed in Seethapathi et al.[32]).

Three important barriers have precluded clinical applications of pose estimation. First, it is not known how well these approaches track and measure movement in clinical populations (e.g., persons post-stroke) where motor deficits, assistive devices, and out-of-plane compensatory movements may make tracking and analysis more difficult. There is a need for large-scale validation and feasibility studies to demonstrate the clinical potential of this technology. Second, there is a need for accessible software that can be used with minimal technical expertise. Current algorithms require at least some degree of computer programming acumen to install and execute. Third, there is a paucity of data and awareness about potential clinical applications of pose estimation.

Only a handful of studies have explored clinical applications in humans (recently reviewed in Stenum et al.[33]), although this number will likely grow rapidly in the coming years. Existing applications of pose estimation in stroke populations are in their nascency and have focused on estimating spatiotemporal gait parameters in small samples of persons post-stroke.[34,35] Many other computer vision-based approaches have been used to measure movement in persons post-stroke (some examples reviewed in Souza et al.[36]), although most of these require specialized equipment (e.g., a Microsoft Kinect device) that is inherently less accessible than video-based techniques like pose estimation.

Of note is the fact that most existing pose estimation algorithms require intensive computing capabilities. Depending on the duration and complexity of the video recording and desired output (e.g., hand-only tracking *vs.* full-body tracking), a graphics processing unit may be necessary for time-efficient analysis. Real-time movement tracking is also available in some algorithms (e.g., OpenPose[25]) but is particularly computationally intensive. Therefore, although only a simple video is needed as an input into the pose estimation algorithm, current algorithms often require significant computing power to perform the quantitative kinematic tracking. Fortunately, there are free resources available (e.g., Google Colaboratory) that can provide this computing power remotely if the user does not own a graphics processing unit.

POTENTIAL APPLICATIONS OF HUMAN POSE ESTIMATION IN POST-STROKE MOTOR ASSESSMENT

Why Use Pose Estimation to Measure Movement After Stroke?

There are several reasons that automated video-based motor assessments could significantly improve care for persons post-stroke. First, frequent motor assessment is critical for tracking recovery and rehabilitation progress after stroke. Current standards for post-stroke motor assessment (e.g., Fugl-Meyer Assessment[15,37] and Action Research Arm Test[38,39]) rely upon subjectively rated ordinal scales that require a trained clinician to manually inspect and rate the performance of many simple movement tasks and aspects of motor function or impairment. Many of these are largely kinematic in nature and could be captured using pose estimation, including assessments of movement speed, amplitude, and range of motion. The reliance upon the time and expertise of the clinician limits the frequency with which motor assessments can be performed, thereby limiting information about the trajectory of the patient's recovery and/or rehabilitation. Pose estimation provides an avenue for fast, accurate, and objective measurement of motor function in persons post-stroke.

Second, persons post-stroke often exhibit a wide variety of motor deficits that vary in type and severity.[5,6,37,40–42] Many persons post-stroke exhibit impairment in fine motor control and gait, but these impairments are difficult to assess quantitatively in clinical settings without access to expensive, research-grade motion capture equipment. Furthermore, accessible tools for quantitative in-home measurement of movement kinematics are not currently available. There is clear potential for pose estimation to offer new approaches for precise measurement of motor function post-stroke using accessible, affordable technologies that are commonly available within the home and clinic (e.g., smartphones and tablets).

Third, many post-stroke motor assessments are performed using validated tasks that necessitate clinic visits because they require interaction with specific objects (e.g., Nine-Hole Peg Test,[43] Purdue Pegboard,[44] and Box and Block Test[45]). Beyond the necessity of an in-person clinic visit, these types of assessments have several other important limitations. Some clinics may have access to only some of these assessment materials but not others; training is often required to administer the assessment appropriately; and some assessments can take considerable time to administer (especially if the patient demonstrates severe impairment and completes subtasks of the assessments very slowly). There is a need to improve the flexibility of motor assessments to promote accessibility in a wider range of environments. Validation of pose estimation approaches for tracking movements involved in these clinical standards against ground-truth measurements and commonly used clinical assessments could lead to the development of remote assessments that approximate these object-based tests without the need for the objects themselves or an in-person clinic visit.

What Aspects of Movement Could Be Measured?

Pose estimation has the potential to capture aspects of post-stroke motor impairment that are observable in movement kinematics. Although many devices exist for measuring movement kinematics outside of the clinic (e.g., wearables, computer vision-based gaming systems), pose estimation could provide significant advantages over existing remote monitoring devices in that the data are inherently "raw" (i.e., there is considerable flexibility in what can be measured) and, importantly, no equipment is required beyond a simple video recording device. This subsection discusses three primary areas of potential application: (1) fine motor control of the hand and fingers, (2) arm movements, and (3) gait (Fig. 2).

Many persons post-stroke exhibit kinematic deviations in movements of the paretic hand[3,4,46–53] that result from impairments in fine motor control. Deficits in control can be quantified by measuring the ability to perform skilled and/or functional movements with the fingers[39,45,54–56] or by testing the ability to individuate movements of one finger from another.[3,4,46,47,57] Many key aspects of these assessments—flexion and extension of individual fingers, closing the fingers and thumb in a precision grip, opening of the hand, and movement of the fingers in isolation of one another—can be captured in movement kinematics and could lend well to assessment via pose estimation. It was recently shown that several relevant tasks—hand opening and closing, hand pronation and supination, and finger tapping—can be tracked accurately using pose estimation in healthy young adults,[58] although this approach has not yet been validated in persons post-stroke.

Beyond confirming existing assessments, video-based pose estimation also holds promise for filling existing gaps in

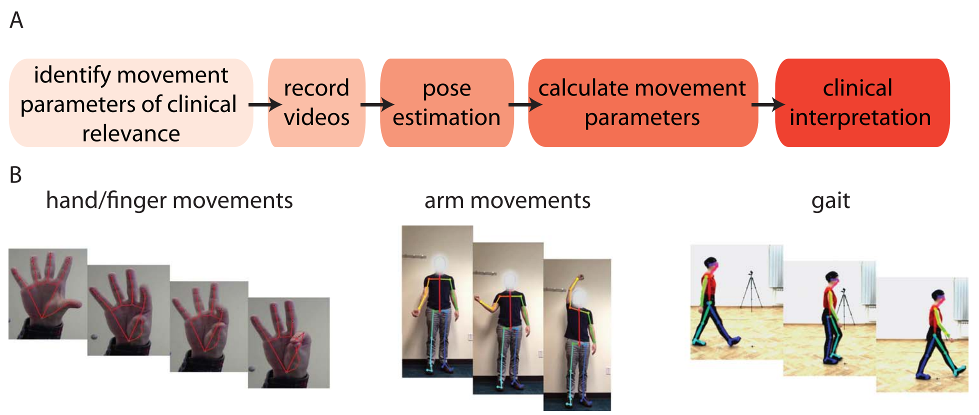

FIGURE 2. A, General workflow for using pose estimation for measurement of clinically relevant movement kinematics. B, Example applications for using pose estimation to track movement kinematics with clinical relevance for persons post-stroke.

post-stroke dexterity assessment. Clinical assessments of dexterous hand movements often use ecologically sound tasks (e.g., precision grip and object manipulation) at the expense of granularity. On the other hand, laboratory-based kinematic/kinetic assessments with higher granularity often ignore key aspects of real-world dexterous control. For example, most assessments of finger individuation rely on devices that only assess movement in one or two dimensions (e.g., finger flexion and extension) but omit other movements that are key aspects of hand dexterity (e.g., abduction/adduction and circumduction). One study using the Cyber Glove (Virtual Technologies, Palo Alto, CA) showed that abduction and adduction were more impaired than flexion/extension in persons post-stroke.[4] However, the Cyber Glove also has limited resolution. For instance, it does not accurately assess middle finger abduction/adduction, and the measured ranges of motion for all the finger joints were consistently much smaller than those assessed without wearing the glove.[4] Moreover, individuation impairment assessed using the Cyber Glove is only minimally correlated with clinical assessment of hand function.[4,59]

Because of the lack of granularity of these assessment tools, it is difficult to determine the relationship between individuation and other hand functions. One reason for this difficulty is that motor control variables omitted from these assessments—such as movement direction, velocity, and spatial and temporal coordination across fingers—may play essential roles in functional everyday activities. Another possible reason is that clinical assessments often quickly reach a ceiling when residual deficits can only be detected by kinematic/kinetic measures. These fine-grained analyses become more informative with respect to dexterous control, where the motor repertoires push the boundary regions of the neural/biomechanical constraints.[60] Detection of these subtle impairments is critical in determining the true recovery of those repertoires *vs.* compensation after stroke. For example, persons post-stroke have demonstrated impairment in anticipatory shaping of hand posture in a reach-and-grasp task and exhibited a compensatory strategy of increasing metacarpophalangeal joint flexion to adjust to different object shapes.[61]

Movements of the paretic arm are also impaired in many persons post-stroke.[41,62–66] Persons post-stroke commonly show kinematic deviations in reaching movements,[41,67] including impairments in velocity, path curvature, index finger end-point, and joint individuation of shoulder, elbow, and wrist. Interestingly, joint individuation was the best predictor of kinematic properties such as reaching path curvature and end-point error.[68] Video-based pose estimation may be an accessible tool for capturing these kinematic features. Furthermore, such analyses may provide richer kinematic information than can be obtained in most current clinical settings, allowing clinicians and researchers to directly relate these measures with clinical assessments. For example, the Fugl-Meyer Assessment of Upper Extremity impairment after stroke underscores impairment in out-of-synergy joint movements (e.g., joint extension, shoulder elevation/retraction/abduction/rotation, forearm pronation/supination, wrist circumduction).[15] These assessments often cannot be fully captured by laboratory-based motion capture systems, and clinical scores lack granularity and are based on subjective visual inspection. Pose estimation may have the potential to extract detailed kinematic information with a higher level of granularity than Fugl-Meyer scores, although the accuracy of this approach has yet to be tested. However, also note that pose estimation will not be able to capture other important aspects of hand dexterity, including sensory feedback,[69] and force production.[70]

Finally, more than half of persons post-stroke have residual gait impairments even after prolonged rehabilitation.[71] Gait dysfunction is heterogeneous and idiosyncratic after stroke: deficits are apparent in a variety of leg joint movements (e.g., stiff knee and foot drop[5,6,72–76]), spatiotemporal gait parameters (e.g., shortened paretic stance time and asymmetric step lengths[5,7,77,78]), and measures of global gait function (e.g., slowed walking speed[6,78]). Many clinical facilities rely on either subjective visual inspection of gait or devices like wearables or instrumented gait mats that provide only limited and predefined gait metrics (e.g., spatiotemporal parameters but little/no information about whole-body gait kinematics). However, it is possible that many (if not all) of the deficits in kinematics and spatiotemporal gait parameters mentioned above could be measured using movement tracking via pose estimation. Indeed, recently developed pose estimation–based gait analysis workflow demonstrated accurate measurement of a wide variety of gait parameters in healthy adults[79] and others have shown preliminary data suggesting that similar approaches can accurately estimate selected gait parameters in persons post-stroke.[34,35] Similar to the other domains of movement that we have discussed previously, there is a clear need for larger validation studies in persons post-stroke; however, early results suggest exciting potential for assessing post-stroke gait using pose estimation-based gait analysis.

POTENTIAL APPLICATIONS OF HUMAN POSE ESTIMATION IN REHABILITATION AFTER STROKE

The ability to measure movement kinematics via pose estimation has the potential for significant impact on post-stroke rehabilitation practice. First, it can provide clinicians with a readily accessible tool to gather quantitative data about movement quality, thus generating a more comprehensive picture of a patient's movement status and changes to that status that occur during rehabilitation. Traditionally, precise kinematic data were unavailable to clinicians as they required expensive and sophisticated three-dimensional motion analysis hardware and software to obtain. Typical clinical outcomes focus on whether a person can execute a functional task (e.g., Can a person pick up a cup to drink? How many steps does a person take in a day?), with only sparse observation-based information gathered about *how* a person completes the task (e.g., movement quality). However, during a recent "Stroke Recovery and Rehabilitation Roundtable," experts agreed that there is an urgent need to include movement quality measures (e.g., kinematics) in stroke rehabilitation trials.[80]

Several studies support the need for inclusion of movement quality measures in post-stroke rehabilitation. For instance, upper extremity kinematics in persons post-stroke (e.g., movement time, trajectory length, directness, smoothness, and trunk displacement) were sensitive to change over time, correlated with single time point upper extremity Fugl-Meyer scores, and associated with clinically meaningful improvements.[81–84] Similarly, lower extremity kinematics—particularly those of the paretic leg—are correlated with measures of gait function and may be used to identify individuals with continuing gait deficits,[85] despite appearing fully "recovered" on traditional scales of gait function (gait speed).[86,87] Thus, quantitative movement analysis is an important clinical tool for assessing pathologies and could provide real-time indicators of patient recovery with improved accuracy when compared with reliance on clinical scores.

Second, pose estimation stands to advance the field of post-stroke rehabilitation by allowing clinicians and researchers to "see behind the curtain" into how people move in the real world and better understand the real-world impact of clinical interventions. Because pose estimation requires only a simple video that can be recorded using household devices, there is significant potential for measuring patient kinematics during natural behaviors directly in the home or other community setting. Improving real-world performance is the ultimate objective of rehabilitation, and clinicians and researchers operate under the assumption that a person's in-clinic movement abilities directly reflect how he/she moves in daily life. However, recent evidence challenges this assumption. Indeed, clinical motor capacity and real-world motor performance of the paretic arm have been found to be incongruent in persons post-stroke.[88] Pose-estimation movement analysis obtained during real-world activity may help clinicians understand to what extent movement and movement improvements exhibited in the clinic reflect movement in the home and contribute to more naturalistic accounts of meaningful changes during post-stroke rehabilitation.[89]

Finally, pose estimation–based movement analysis can be incorporated into a growing realm of rehabilitation: telerehabilitation (Fig. 3). Telerehabilitation—the delivery of rehabilitation in the home via videoconferencing—has emerged as a promising mode to overcome access to in-person care.[90] Home-based stroke rehabilitation is safe and provides important insight about environmental factors that influence mobility. As in in-person post-stroke rehabilitation, a critical element of effective telerehabilitation is the ability to collect quantitative data about an individual's movement.[91] A number of recent technologies have aimed to meet this need. For instance, body sensors can identify the type and quantity of movement during practice or daily routines.[92] Microsoft Kinect and virtual reality systems are able to track reaching and grasping movements within a defined area.[93,94] Pose estimation–based movement analysis can be used in conjunction with these other remote monitoring tools but has the advantage of not requiring

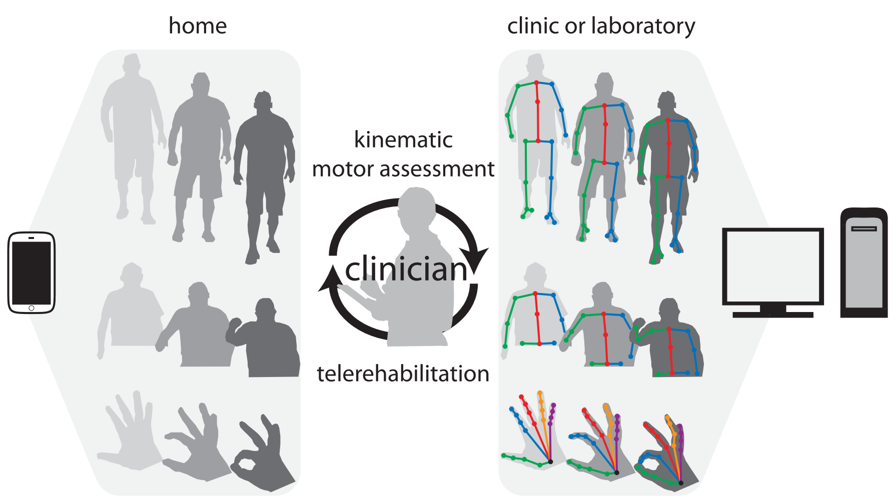

FIGURE 3. Conceptual diagram showing a clinician-centered approach for using pose estimation to measure in-home movement kinematics and, in turn, leveraging these data to facilitate in-home telerehabilitation.

any equipment beyond the patient's own recording device to capture the data. Together, these technologies will allow frequent, precise data acquisition that can be used to individualize care and improve post-stroke rehabilitation.

WHAT'S NEXT?

Before widespread implementation of pose estimation tools for measuring movement after stroke, there is a need to understand (1) how well these tools can capture common post-stroke motor deficits and (2) best practices regarding how videos should be recorded to capture specific deficits. This validation and feasibility work is ongoing,[34,35] but significantly more research is needed to optimize the use of pose estimation for post-stroke motor assessment. In particular, there is an unmet need for studies of pose estimation applications for capturing motor deficits in the paretic hand and arm. Specifically, it remains to be determined how sensitive pose estimation is in capturing digit individuation and movements of exceptionally small ranges of motion.

There are also a variety of human factors and infrastructure barriers to clinical implementation of these technologies that are discussed at length in a previous review.[33] Briefly, pose estimation technologies need to become more user-friendly for persons without technical backgrounds, provide easily interpretable outcome measures with direct clinical relevance, and become more accessible to groups that do not have access to high-powered computing resources. Clinical applications of pose estimation technologies will likely not become widely used until these barriers—which are largely addressable—are overcome.

CONCLUSIONS

Pose estimation has the potential to make a significant impact on the way that movement is measured and care after stroke is delivered. The ability to capture clinically relevant movement kinematics using a household video recording device could lead to the development of widely accessible tools for quantitative post-stroke motor assessment that could be performed in virtually any setting, including directly in the home or clinic. Furthermore, there is opportunity to leverage pose estimation tools to deliver telerehabilitation interventions that target movement quality directly in patient homes. It is anticipated that these technologies will play a prominent role in the future of digital medicine and remote monitoring of motor function in persons post-stroke.

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