21 Wearable Sensors for Stroke Rehabilitation

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Abstract

In this chapter, we provide a review of the current applications of wearable sensors in the field of stroke rehabilitation. Four key points are discussed in this review. First, wearable sensors are a viable solution for monitoring movement during rehabilitation exercises and clinical assessments, but more work needs to be done to derive clinically relevant information from sensor data collected during unstructured activities. Second, wearable technologies provide critical information related to the performance of activities in daily life, information that is not necessarily captured during in-clinic assessments. Third, wearable technologies can provide feedback and motivation to increase movement in the home and community settings. Finally, technologies are rapidly emerging that can complement "traditional" wearable sensors and sometimes replace them as they provide less obtrusive means of monitoring motor function in stroke survivors. These developing technologies, as well as readily available wearable sensors, are transforming stroke rehabilitation, their development is progressing at a fast pace, and their use so far has allowed us to gather important information, that we would have not been able to collect otherwise, which has tremendous potential to further advance stroke rehabilitation.

Keywords

Stroke · Upper limb · Neurorehabilitation · Clinical assessment · Movement tracking · Wearable sensors · Outcome measures

Abbreviations

10 MWT	10-M walk test
ADL	Activity of Daily Living
ARAT	Action Research Arm Test
BBT	Box and Block Test
Cis	Confidence intervals
EMG	Electromyography
FAS	Functional Ability Scale (subscale of the Wolf Motor Function Test)

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FMA-UE	Fugl-Meyer Assessment, Upper Extremity subsection
ICF	International Classification of Functioning, Disability and Health
IMU	Inertial Measurement Unit
IoT	Internet of Things
LL	Lower Limb
MAL	Motor Activity Log
MLA	Machine Learning Algorithms
MMG	Mechanomyography
RFID	Radio Frequency IDentification
RMSE	Root Mean Square Error
SARAH	Semi-Automated Rehabilitation at the Home
TIS	Trunk Impairment Scale
TUG	Timed Up-and-Go
UL	Upper Limb
UWB	Ultra-WideBand
WMFT	Wolf Motor Function Test

21.1 Introduction

Wearable sensors could be used in many ways in stroke rehabilitation. They could be used to perform clinical assessments, facilitate the design of patient-specific rehabilitation strategies, enable the delivery of high-dosage interventions, and track clinical outcomes. The use of wearable sensors could help rehabilitation specialists to address the increasing demand and decreasing access to rehabilitation care that the shortage of rehabilitation specialists is expected to cause [1]. Tracking the response of each patient to the prescribed intervention would allow therapists to carefully adjust the intervention strategy throughout the therapy period and achieve optimal clinical outcomes on a patient-by-patient basis. Furthermore, wearable sensors could help rehabilitation specialists to deliver interventions in the home setting and to monitor subjects in the community, thus reducing the therapists' workload and facilitating the delivery of long-term interventions that may be most effective in maximizing motor gains. Figure 21.1 shows a schematic representation of how we envision that wearable sensors could be applied across the continuum of care.

The material in this chapter is organized in the following four parts:

- Monitoring stroke survivors during the performance of rehabilitation exercises and clinical assessments.
- Monitoring stroke survivors during the performance of activities of daily living (in the home and community settings) with the goal of capturing what patients "do" as opposed to what they "are capable of doing".
- Monitoring stroke survivors to generate feedback and provide motivation to maximize the amount and quality of motor practice.
- Monitoring stroke survivors using emerging technologies that overcome the limitations of "traditional" wearable sensors and systems.

Herein, we will primarily focus on upper-limb (UL) rehabilitation after stroke (i.e., arm and hand movements), though in some sections of the chapter, we will provide insights into the use of wearable technology to monitor and enable lower limb rehabilitation (i.e., balance and mobility training). In each section, we will elaborate on the clinical importance of the applications discussed, provide examples of what has been accomplished so far, and suggest how these technologies should be integrated into the clinical workflow in the future. While this chapter is focused on stroke rehabilitation, many of the applications of wearable technology herein discussed are relevant not only to designing interventions for other neurological diseases, but also to geriatric and musculoskeletal rehabilitative care.

Because we anticipate an interdisciplinary readership, in the box below, we provide the definitions of a few terms utilized throughout this chapter to facilitate a common understanding of the used terminology.

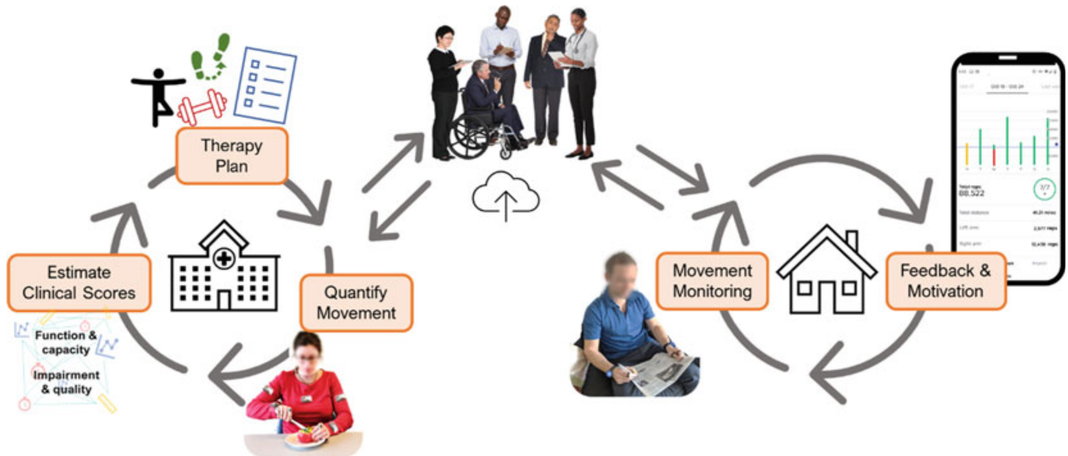

Fig. 21.1 Conceptual representation of the application of wearable sensors across the continuum of rehabilitation care. In the clinic (left), sensors are used to measure movement patterns during the rehabilitation sessions. Sensor data is used to estimate clinical scores and evaluate progression. This information is used to adjust the therapeutic plan. In the home environment (right), sensors can be used to monitor patients' movements as well as provide feedback and motivation to keep practicing in order to improve motor performance. Clinicians and engineers who are part of the care team (top) are given access to the data to make informed decisions

ICF domain definitions and their link with other common terms used across disciplines

Impairment: is a deficit in body structure or function. Example: a loss of muscle strength, or somatosensation in the upper limb post stroke. It is the accumulation of a few or many impairments that lead to limitations in the capacity for and performance of the activity. Common clinical tests to measure impairment in rehabilitation: Fugl-Meyer Upper Extremity test, grip strength, monofilament testing.

Capacity for activity: is the execution of an activity in a structured environment, such as in the clinic or a laboratory. Other common terms used to describe the same idea include "function", "functional capacity", and "capability". Examples: activities such as dressing, typing or walking. Common clinical tests to measure upper limb capacity in rehabilitation: Action Research Arm Test, Wolf Motor Function Test, Box and Block Test.

Performance of activity: is the execution of activity in the unstructured, real-world environment, that is measured in the home and/or community with the existing facilitators and barriers. Examples: activities such as cooking or bathing in the home environment (that might or might not have been modified after the stroke). Common ways to measure upper limb performance: motor Activity Log (self-perceived measure) and accelerometry (direct measure).

Participation: is the fulfillment of life roles and responsibilities. Participation typically requires the performance of multiple activities in the motor, cognitive, and language domains. Examples: caring for a child or working. Common clinical tests to measure participation: stroke impact scale and Neuro-Quality of Life.

21.2 Wearable Sensors for Assessments Performed in the Clinic

21.2.1 Why Would One Want to Use Wearable Sensors for Assessments Performed in the Clinic?

Numerous studies have shown that rehabilitation interventions are beneficial across a number of neurological conditions as they result in a decrease in the severity of disability [2]. However, choosing the most effective intervention among the myriad of available rehabilitation approaches is challenging [3, 4]. High variability in the response to interventions aimed to restore UL function is observed across patients [5, 6], hence pointing to the need for designing “precision rehabilitation” interventions that account for the unique characteristics of each individual. The need to develop patient-specific interventions is paramount in the broad field of medicine [7–9] and is gradually emerging as a topic of great interest in the field of rehabilitation as investigators explore approaches relying on patients’ genotype [10–12] and motor phenotype [13–15] to develop subject-specific interventions.

In this context, it is important that rehabilitation specialists be provided with tools to monitor the motor recovery process, assess if the ongoing intervention is leading to the anticipated clinical results, and adjust the intervention if needed. Interventions are typically structured according to the ICF model [16]. Rehabilitation specialists use this framework to evaluate interventions and rely on clinical outcome measures to capture different ICF domains (i.e., *Body Function and Structures*, *Activity*, and *Participation*). Clinical outcome measures are often based on the observation of subjects’ motor behaviors (e.g., to capture motor impairments and activity limitations). Unfortunately, these methods suffer from several shortcomings. For instance, only a limited number of rehabilitation specialists undergo the rigorous training needed to properly administer these evaluations. Despite training, substantial inter-rater variability is frequently observed. Besides, oftentimes clinical scales are prone to subjectivity and are marked by low resolution, and hence limited ability to capture change. These assessments are also time-consuming and can be impractical to administer on a regular basis throughout the period of intervention.

Outcome measures are too many times collected only at baseline and at discharge. This is a problem because the lack of longitudinal data tracking progression prevents rehabilitation specialists from examining the potential need to adjust the intervention to maximize motor gains. To address this problem, researchers and clinicians have started to explore the use of wearable sensing technology to collect longitudinal data and derive estimates of clinical outcome measures (i.e., clinical scores). Over the past decade, wearable technology has matured to the extent needed to provide clinicians with an effective tool to monitor outcomes and facilitate delivering interventions [17–20]. This technology has tremendous potential for assessing the benefits of rehabilitation interventions [21]. Wearable sensors are a ubiquitous and unobtrusive tool to quantify movement, gather important data during the administration of clinical assessments, and track motor behaviors during an intervention period to monitor progression.

21.2.2 Assessing Arm and Hand Movements of Stroke Survivors in the Clinic

21.2.2.1 Estimating Movement Kinematics

Most ADLs require the performance of reaching movements, which are marked in stroke survivors by greater trunk movement and limited elbow extension. Nonetheless, clinical tests often fail to measure a range of motion during the performance of motor tasks. Kinematic assessments are considered a gold standard for objective evaluation of movement. In stroke rehabilitation, it is important to capture movement characteristics and deficits in order to refine and evaluate interventions [22]. However, kinematic evaluations in the clinic are limited due to the lack of time, training, cost, and equipment needed (i.e., marker-based optical tracking systems). Over the past decades, quite a few approaches marked by different levels of complexity have used wearable IMUs to track limb movements. For instance, methods have been developed that allow one to reconstruct the kinematics of movement from accelerometer, gyroscope, and magnetometer data recorded using sensors placed on different body segments. Kinematic analysis with wearable sensors has been shown to be an objective, sensitive to change, and quantitative means of measuring motor impairment. A review of all the approaches proposed so far is beyond the scope of this chapter. Herein, we provide instead examples of clinical applications of these technologies.

For example, Schwarz et al. [23] used a portable IMU system to measure UL kinematics. A total of eight IMUs and sensors were placed on the upper body, including a fingertip force-sensing resistor to detect interaction forces between the object and the fingers. Data was collected during the performance of functional reach-to-grasp and object displacement tasks. The authors were able to extract parameters such as trunk compensation, shoulder flexion-extension and abduction-adduction, elbow flexion-extension, forearm supination-pronation, wrist flexion-extension, and flexion-extension of the fingers. In addition, the authors found evidence of joint coupling during the performance of object displacement tasks via the analysis of the correlation between elbow flexion-extension and trunk movements.

Hand function is important for the performance of ADLs, but hand kinematics is difficult to collect. Gloves instrumented with IMUs and magnetic sensors can be used to reconstruct joint motion and provide clinicians with valuable information [24]. Using this type of system in the clinical setting is attractive but has major drawbacks such as the interference with tactile and proprioceptive feedback when manipulating an object, sanitation concerns if the sensors are used by multiple patients and the time required to properly don/doff the glove. Researchers have investigated a novel method of finger movement tracking based on wearable capacitive strain sensors to address some of the glove's limitations [25]. Other emerging technologies will be discussed in Sect. 21.5 of this chapter.

More recently, Nie et al. [26] reported the use of a portable, open-source solution to estimate the position of the wrist during reaching movements with two IMUs. Their method allows one to track the wrist position and average active range of motion during reaching movements with relatively high accuracy (within 1.0–2.5 cm) compared to a marker-based optical tracking system. In addition, a sweeping task allowed the authors to derive two different clinically relevant metrics. The horizontal sweep area "(i.e., reaching workspace)" and the smoothness of the sweeping movement are indicative of movement impairments (smoother movements indicate less impaired UL following a stroke). To improve the clinical implementation of such measures, the authors purposefully decided to make their methods available and transparent for others to use with any sensor capable of estimating limb orientation.

So far, the research findings support the clinical suitability of sensor-based motion analysis to track UL movements in stroke survivors. However, the implementation of such methods outside the research setting remains to be tested.

21.2.2.2 Estimating Clinical Scores

Over the past two decades, researchers have increasingly incorporated the use of wearable sensors into their stroke rehabilitation work [27], both to measure UL activity in the home and to add to the traditional methods of assessments in the clinic. Several research groups have studied the use of IMUs to assess motor function more objectively, some as a way to automate or instrument the assessment of motor function in the clinical setting, others to derive UL motor impairments by estimating various clinical scores from data collected during the performance of predefined motor tasks.

Fig. 21.2 Conceptual representation of methods commonly used to estimate clinical scores. Data is collected with wearable sensors positioned on the upper limbs during the performance of functional tasks. Accelerometer data is fed to a machine learning algorithm to derive estimates of the clinical scores of interest. Reproduced and modified with permission from Adans-Dester et al. (https://doi.org/10.1038/s41746-020-00328-w, licensed under CC BY 4.0)

Figure 21.2 represents a methodology to derive clinically relevant information from wearable sensors. First, different combinations of wearable sensors are used to collect data sometimes during the performance of the clinical test itself, other times during specific tasks or general arm movements. Then, data are processed using machine learning algorithms (MLA) to derive estimates of the outcome of choice. Here, we provide some examples of clinical score estimates relevant to stroke rehabilitation.

Fugl-Meyer Assessment

The Fugl-Meyer Assessment, Upper-Extremity subscale (FMA-UE) is a clinical test designed to evaluate motor impairments that have been tested extensively in the stroke population [28]. A total of 33 items assessing voluntary movement, reflexes, grasp, and coordination are tested; each item is rated on a 3-point ordinal scale.

The first method to derive the FMA-UE scores is the instrumentation of the test with wearable sensors. For example, researchers used two accelerometers and seven flex sensors to monitor the movements of the UL during the performance of 7 movements derived from the FMA-UE [29]. They used MLA to predict the FMA scores based on wearable sensor data and demonstrated the possibility to achieve a coefficient of determination as high as ~ 0.92. Considering that the FMA scale is time-consuming and complicated to perform, using only seven items of the FMA reduces the time to gather data as long as the patient's impairments allow for easy donning and doffing the sensors.

Another method is to use data collected during the performance of functional tasks. Del Din et al. [30] selected a subset of eight tasks from the Wolf Motor Function Test (WMFT) and used six accelerometers placed on the affected arm and the trunk. They used a Random Forest MLA to estimate FMA-UE scores. Their results were marked by a root mean squared error (RMSE) of 4.7 points of the FMA-UE.

Some have tried to combine inertial measurement and mechanomyography (MMG) to better quantify hand and wrist motor function during the estimation of FMA-UE scores. Researchers used 3 IMUs (torso, arm, and forearm) and MMGs placed on finger and wrist flexors to collect data during the performance of FMA-UE tasks. Unfortunately, the detection of the tasks performed by study volunteers was marked by only 75% accuracy for gross movements and 62% accuracy for distal motor tasks (hand and wrist) [31]. These results are not encouraging, not only because of the relatively low accuracy, but also because the data was collected during the performance of the clinical test. Therefore, in this scenario, wearable sensors did not streamline the clinical evaluation.

Functional Ability Scale

The Functional Ability Scale (FAS) is used to assess the quality of movement via observation of the performance of the items of the Wolf Motor Function Test (WMFT). The WMFT is commonly used to quantify UL motor function with timed functional tasks [32]. It consists of 17 items progressing from proximal to distal and from least to most complex UL movements. Each item is used to assess speed and movement quality. The FAS relies on a 6-point ordinal scale to rate the quality of the movement observed by the clinician.

Patel et al. [33] used accelerometers placed on the hand, forearm, upper arm, and trunk to collect data during the performance of a subset of eight motor tasks taken from the WMFT and derive accurate estimates of the total FAS scores provided by a clinician. They showed that it is possible to achieve estimates of the total FAS score marked by a bias of 0.04 points on the scale and a standard deviation of 2.43 points when using as few as three sensors to collect data during the performance of six motor tasks.

Box and Block Test

The Box and Block Test (BBT) is commonly used to measure manual dexterity. The BBT is scored by counting the number of blocks carried over a partition from one compartment to another over one minute [34]. During the investigation of the MusicGlove, a sensorized glove was used to retrain hand function by playing games similar to "Guitar Hero", researchers found that the MusicGlove game scores are strongly correlated with the BBT scores [35].

Action Research Arm Test

The Action Research Arm Test (ARAT) is a common activity level (capacity) measure used in stroke rehabilitation studies. The test has four subscales to evaluate gross motor, grasp, grip, and pinch. An ordinal scale is used by the clinician to score the observed ability and quality of the task performance. To enhance objectivity and provide additional information on capacity, Resnik et al. instrumented the ARAT test using IMUs and EMG sensors [36]. Five parameters associated with the ARAT were derived (movement time, smoothness, hand trajectories, trunk stability, and grasping muscle activity). They found a strong correlation between the ARAT scores and the movement time and smoothness. While the instrumented ARAT allows one to quantify movement parameters and might provide a better insight into arm motor function, it is quite cumbersome to administer, and the data processing remains lengthy.

To address some of these limitations and to set the preliminary groundwork for evaluating UL outside the clinic, Bochniewicz et al. used a single IMU at the wrist during the performance of four ADL tasks (i.e., laundry and kitchen activities, shopping, and making a bed) [37]. The authors trained a MLA to distinguish between functional (i.e., manipulating an object) and non-functional tasks (i.e., arm swing while walking). The percentage of time spent using the arm to accomplish a functional task was correlated with the ARAT scores. The authors noted the shortcomings of using only one IMU at the wrist for ADLs requiring little to no arm movements.

Estimating More than One Clinical Scale

Adans-Dester et al. estimated two different clinical scores from the same dataset [38]. The authors developed machine learning-based algorithms to estimate FAS and FMA-UE scores via the analysis of accelerometer data collected during the performance of functional motor tasks, that are part of the Wolf Motor Function Test (Fig. 21.3 a). The accelerometer data was segmented to select epochs associated with the performance of specific movement components (e.g., forward arm reaching, pronation-supination movements). Data features were derived from each epoch and fed to a machine learning algorithm based on a regression implementation of a Random Forest. Separate models were built to estimate the FAS

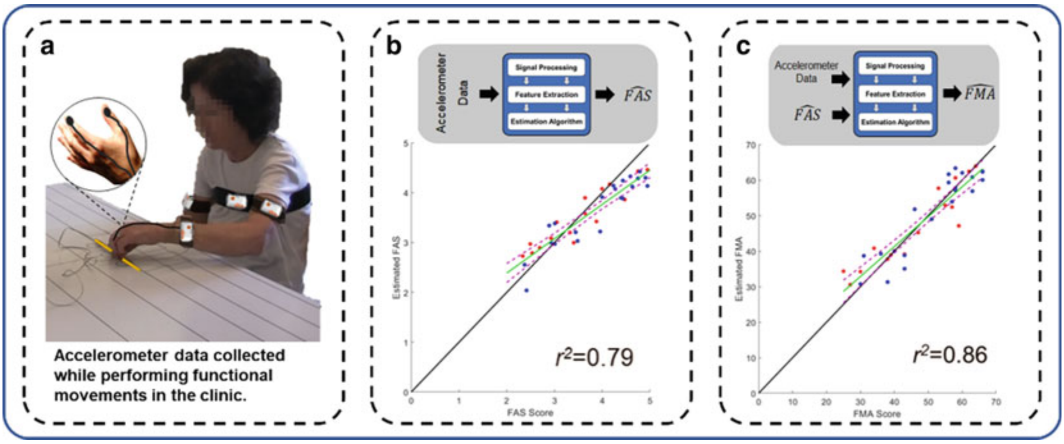

Fig. 21.3 Data collected using accelerometers during the performance of functional tasks (panel A) were used to derive estimates of the FAS (panel B) and the FMA-UE (panel C) clinical scores. Reproduced and modified with permission from Adans-Dester et al. (https://doi.org/10.1038/s41746-020-00328-w, licensed under CC BY 4.0)

and the FMA-UE scores. FAS estimates were marked by an RMSE of 0.38 points and a coefficient of determination (r^2) of 0.79 (Fig. 21.3b). The magnitude of the estimation error was deemed satisfactory, especially given the exploratory nature of the study. For the FMA-UE estimates, the authors used the output of the FAS estimation algorithm as an input to the FMA estimation module. The RMSE was equal to 3.99 points with a coefficient of determination (r^2) equal to 0.86 (Fig. 21.3c). This work is especially relevant to an application in the clinic as with one set of functional tasks, researchers were able to accurately estimate a measure of impairment and one of movement quality.

All the examples discussed above show the feasibility of deriving estimates of clinical scores via the analysis of data collected using wearable sensors. However, these techniques require going through the clinical test items or through a list of predefined motor tasks, which does not help to reduce the burden of administering evaluations. In addition, data processing remains labor-intensive in several of these cases. We hope that, in the future, researchers will find a way to derive clinical scores from wearable sensor data collected during the performance of unstructured activities and to streamline the analysis of such data. As such, using wearable sensors to estimate clinical scores would not only reduce the time needed to perform clinical assessments, but also allow clinicians to evaluate the effects of the intervention more regularly, facilitate the documentation of patients' response to the intervention, and adjust rehabilitation interventions as required to better meet the needs of their patients.

21.2.2.3 Wearable Sensors to Facilitate Upper Limb Training in the Clinic

The *ArmeoSenso* (Hocoma, Switzerland) is an example of a commercially available system for rehabilitation using wearable sensors [39]. Three IMUs are attached to the forearm, upper arm, and trunk to track arm movements in a three-dimensional space. The tracked UL movements serve as input for therapy games. Using such systems can enable group training in the clinic, allowing therapists to treat several patients simultaneously and potentially reduce therapy costs. Although we are not aware of any study using the *ArmeoSenso* for group training, Wittmann et al. [40] provided evidence that the *ArmeoSenso* can be used for self-directed arm therapy and enable high-dosage UL therapy that might result in improvements in arm function.

Also, Widmer et al. [41] used the *ArmeoSenso* in a study in which therapists provided minimum supervision during the training sessions. These studies provide direct evidence of the suitability of the system for self-directed, home-based therapy and indirect evidence of its suitability for group therapy.

The *MusicGlove* is a commercially available instrumented glove that requires the user to practice individual finger and grasping movements to play a music-based video game to retrain hand motor function after stroke (Fig. 21.4). A study comparing conventional UL training to training with the *MusicGlove* in chronic stroke survivors reported improved hand function related to grasping small objects (measured with the Box and Block Test) in the group using the *MusicGlove* [42]. No difference was found between training types for other measures of UL impairment (i.e., FMA-UE, WMTF, force). However, when the device was used for home-based hand therapy and compared to a conventional home exercise program, results showed an improvement in self-reported quality and amount of use (MAL scale) [43]. One of the attractiveness of this device for rehabilitation in the clinic is its low cost (~$2500 for the clinic and ~$350 for the individual version). In addition, the ease of use of the device allows patients to use it by themselves in between therapy sessions or for use in group therapies where a single therapist can oversee numerous patients.

Wearable sensors have also been looked at as a way to provide feedback in the clinic. For example, Arteaga et al. [44] developed and tested a low-cost prototype (~$100) of a wearable device to detect undesired postures in stroke survivors. The system consisted of 10 IMUs to track patients' posture and a combination of beeper, vibration, and LED light to provide feedback. While their pilot study showed the ability of the system to detect bad postures, unfortunately, it lacked testing in stroke survivors and seemed cumbersome to use, based on the number of sensors and equipment needed.

Wearable sensors to deliver rehabilitation interventions also provide an objective way to measure arm and hand movements during therapy. The feedback provided on the movement performance can provide much-needed motivation for stroke patients. It is important to note that the cost-benefit ratio of using wearable sensor-based methods to facilitate UL training in a rehabilitation setting needs to be examined.

Fig. 21.4 The *MusicGlove* is a system that integrates wearable technology and an interactive game (e.g., the Guitar Hero) to train hand dexterity. Reproduced with permission from Flint Rehabilitation Devices, LLC

21.2.3 Assessing and Treating Balance and Mobility of Stroke Survivors in the Clinic

Stroke survivors and others living with neurological diseases often present with balance and gait deficits associated with an increased risk of falls which impacts not only the quality of life, but also increased costs of care due to hospitalizations resulting from a fall [45]. It is, therefore, important for clinicians to quantify those deficits and identify patients at risk. For instance, the discharge plan will be different for patients with severe mobility impairments than those with mild ones. These assessments will also guide the rehabilitation plan and choice of assistive devices necessary for safe ambulation.

21.2.3.1 Estimating Clinical Scores

10-m Walk Test

The 10-m walk test (10 MWT) is used in the clinic to assess walking speed and determine the level of gait impairment following a stroke. The test records the time required to ambulate (often at a self-selected pace) 6 m on a 10-m walkway, the distance is then divided by the time to provide the speed in meters per second. However, this test does not provide any information on the gait quality, which may be problematic as one can walk faster but with compensatory strategies or , on the contrary, walk slower but with a better gait quality. Therefore, some researchers tried to complement the traditional gait speed assessment by using wearable sensors. Bergamini et al. [46] used a set of five IMUs to collect 3D linear accelerations and angular velocities from the pelvis, sternum, and head during the 10MWT performance. The amplitude of the accelerations and the gait symmetry measures they derived can provide the clinician with knowledge of the motor strategies and walking abilities of the patients, which complements the traditional speed information. More recently, Garcia et al. [47] tested the use of only one IMU placed at the waist to derive a gait smoothness metric via the estimation of SPARC (spectral arc length). They identified via the IMU a reduced smoothness (lower SPARC) in stroke survivors, compared to healthy controls. The variability in smoothness during the 10MWT was higher in severely impaired stroke participants. In addition, they found that a smoother gait was correlated with lower limb (LL) spasticity and vice versa. Their results show that IMUs can provide complementary and clinically relevant information to the 10MWT and has the potential to be used in an outdoor environment.

Timed Up-and-Go Test

The Timed Up-and-Go (TUG) test is widely used clinically to evaluate mobility, balance, and fall risks in adults. The instrumented TUG (iTUG) requires patients to walk more than the original, non-instrumented version (7 m vs. 3 m, respectively) but allows one to gather more clinically relevant information than the conventional TUG, which only reports the time to complete the task. Researchers used a set of five IMUs for the iTUG: bilaterally on the wrists, bilaterally on the shanks, and one on the trunk [48, 49]. In addition to the total time, the iTUG can provide a breakdown of the test with the following: sit-to-walk duration and peak velocity, turning duration and peak velocity, and turn-to-sit duration and peak velocity. Gait metrics can also be derived to provide relevant information on the gait quality such as cadence, speed, stride length, and gait asymmetry. Even though it might not be faster than performing instrumented clinical tests, the iTUG allows one to gather more data on movement quality which is not available otherwise with most gait and mobility tests.

Trunk Impairment Scale

Impairments in trunk control often result in decreased balance, increased risk of falls, and can severely affect activities of daily living. In stroke, it can be assessed using clinical outcome measures such as the Trunk Impairment Scale (TIS) [50]. Researchers developed an instrumented version of the TIS with the hope of providing more detailed and clinically relevant information about trunk movement and how it relates to trunk impairments [51]. They used a commercially available system (Valedo, Hocoma, Switzerland) that includes three IMUs to measure trunk movement (in degrees) and velocity of body segments [52]. The system was assessed as a valid and reliable method to estimate trunk movements when compared to using an optoelectronic system in healthy participants [53]. Researchers found a moderate correlation between the instrumented TIS and scores attributed by clinicians. Using the wearable sensor system to instrument the TIS provides more information about trunk movements than the TIS. For instance, the ability to detect small changes in the range of motion that may not be observed clinically [51]. Nonetheless, this system with IMUs only on the trunk cannot account for LL compensatory movements which are commonly used by stroke survivors.

21.2.3.2 Wearable Sensors to Facilitate Gait Training in the Clinic

In the SIRRACT trial, researchers used IMUs bilaterally at the ankles to monitor LL movements performed by stroke survivors during their inpatient stay [54]. The aim of this intervention was to motivate patients and their therapists to engage in more gait practice to obtain improved walking-related outcomes. During this randomized clinical trial, participants followed their conventional therapies while wearing the sensors. Activity summaries (i.e., walking speed, distance, duration) derived from the sensor data was used to provide an augmented feedback intervention that was compared with feedback about walking speed alone. The key findings showed that providing augmented feedback beyond speed alone did not increase the time spent practicing or improve walking outcomes and found that during the inpatient stay, only a modest amount of time was spent walking. The authors pointed out that these results did likely reflect the constraints of inpatient rehabilitation such as space to practice walking and time spent focusing on other aspects of rehabilitation.

Another study by Byl et al. [55] found that providing dynamic visual kinematic biofeedback from pressure sensors and IMUs during gait training had similar effects to verbal feedback provided by the therapist. While these results are not encouraging the use of the system in the clinic when a therapist is available to provide oversight, they demonstrate the potential of using wearable sensors for gait training with limited therapist supervision.

21.2.4 Could Wearable Sensor-Based Evaluations Be Useful to Clinicians? A Possible Future Scenario

If data can be acquired and processed using streamlined procedures, then wearable sensors could enable data to be collected with minimal patients' and clinicians' burdens. These methods could allow clinicians to track the motor recovery trajectory of stroke survivors as schematically represented in Fig. 21.5. The figure shows a hypothetical case in which a patient undergoes a 36-week intervention. During this period of time, wearable sensors are used to monitor the subject. After 18 weeks, clinical score estimates and kinematic parameters derived from the sensor data, are available and define the motor recovery trajectory observed in response to the intervention until that point in time (orange circles in Fig. 21.5). The data can be used by rehabilitation specialists to assess if the patient is responding adequately to the ongoing intervention or if an adjustment to the intervention strategy is needed. Importantly, the information could be used to predict the patient's response to the intervention for the remaining weeks of the intervention period (green circles in Fig. 21.5).

Such models could also account for the patient's clinical phenotype and hence generate predictions based on both the information generated by the wearable sensors and the anticipated response to the intervention based on the patient's clinical characteristics. In this context, the above-described methods could be relied on to assess and predict the effectiveness of a given therapeutic intervention. The approach described in this hypothetical clinical scenario captures the essence

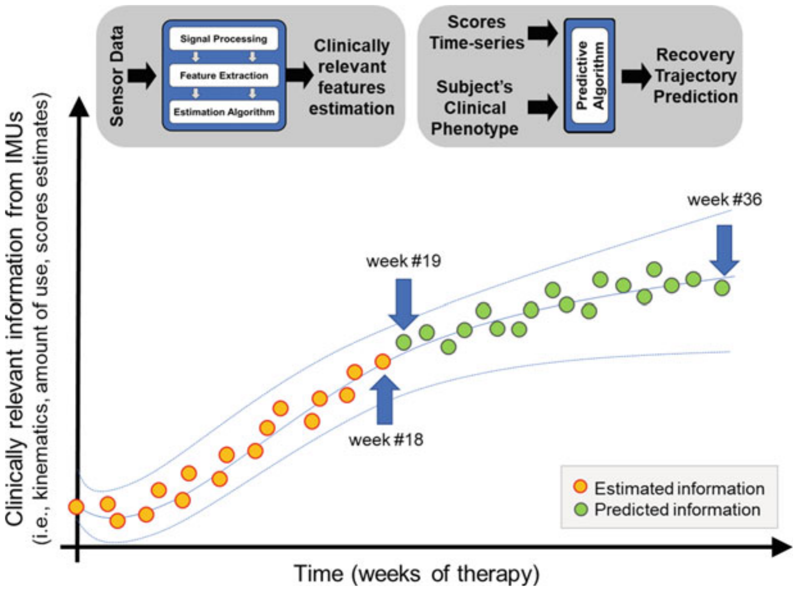

Fig. 21.5 Monitoring the motor recovery trajectory using wearable sensors. The time series represent the recovery trajectory of a hypothetical subject undergoing rehabilitation. The estimated information (orange circles) are clinically relevant measures of arm movements. The predicted information (green circles) is modeled based on the time series of the previously estimated information (orange circles) and the subject's clinical phenotype. Fitting a function (e.g., a polynomial equation) leads to generating a curve that represents the recovery trajectory. In addition, confidence intervals are generated for both the estimated and predicted clinically relevant information. Reproduced and modified with permission from Adans-Dester et al. (https://doi.org/10.1038/s41746-020-00328-w, licensed under CC BY 4.0)

of precision rehabilitation in which clinicians design patient-specific interventions, set clinical objectives, track patient's response using wearable sensors, and periodically evaluate the effectiveness of the ongoing intervention based on the observed recovery trajectory. Future work should fully enable this approach by further improving the unobtrusiveness and ease of use of wearable sensors and by developing fully automated data analysis procedures, for instance, for the segmentation of the sensor data based on detecting data characteristics associated with the performance of motor tasks suitable to derive reliable estimates of clinical scores. Discussing these implementation challenges with patients, clinicians, and engineers during future research and product development will likely result in more widespread and accessible use of wearable sensors in the clinic.

21.3 Wearable Sensors to Measure Movement in the Field

21.3.1 Why Would One Want to Measure Movement in the Field?

The first and simplest answer to this question is because it is movement in the field, i.e., activity performance in everyday life, that persons with stroke care most about. People with stroke are referred to or seek out rehabilitation services to improve the performance of an activity in their home and their community. Indeed, self-identified rehabilitation goals are nearly always (88%) about improving performance in daily life [56]. In contrast, researchers and clinicians rarely place performance of daily activity at the center of their measured treatment goals (Lang et al. unpublished data). Clinicians in the current stroke rehabilitation delivery model focus on measuring impairments and capacity (see Box in the Introduction section for definitions) with the assumption and hope that improvements in these measurement levels will translate to improvements in performance in daily life.

The second answer to this question is that the capacity for movement assessed in the clinic does not necessarily provide accurate and actionable information about the performance of movement in the field. This conflict is illustrated with walking data in Fig. 21.6. The red oval highlights a portion of the data around 0.75 m/s walking speed where some individuals are walking only 2000–4000 steps/day, while others are walking 8000 or even 12,000 steps/day. Without wearable sensors (here attached to the unaffected ankle) quantifying walking performance in the field, neither rehabilitation clinicians nor their patients would know how much walking in the field occurs.

The third answer to why one would want to measure movement in the field is because improvements in movement assessed at the impairment and capacity levels within the clinic often do not translate to improvements in the performance of activities in daily life. Figure 21.7 shows an example of this, where there is a clear improvement over the course of outpatient therapy services on a common standardized test of UL capacity (Fig. 21.7a) but no change in movement performance in daily life (Fig. 21.7b) as measured with wearable sensors in the field.

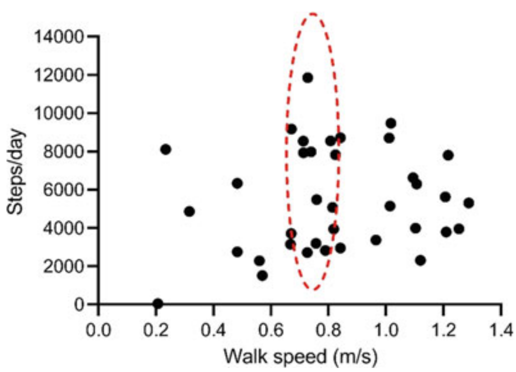

Fig. 21.6 Measures taken in the clinic are not consistently related to measures taken in the field. Scatterplot of people (n = 37) receiving outpatient therapy services post stroke. X-axis: in-clinic measure of walking capacity using the 10 MWT. Y-axis: in the field measurement of walking performance quantified by steps/day. The dashed red oval illustrates how individuals with a small range of walking speeds can have very different amounts of walking in the field. Data from Holleran et al. (https://doi.org/10.1097/NPT.0000000000000327)

Multiple reports have now shown a discrepancy in stroke rehabilitation outcomes in movement capacity assessed in the clinic versus movement performance assessed in the field [57–60]. In a recent analysis (Lang et al., unpublished data, N = 138), the majority (58%) of people receiving outpatient services at five rehabilitation clinics around the United States improved their capacity to complete UL and walking activities, as measured by in-clinic assessments, but failed to improve their movement performance in the field, as measured with wearable sensors. An additional 17% improved both capacity and performance, 24% improved on neither, and 1% improved on performance but not capacity. These data illustrate the point that just because someone can execute actions in a clinic or laboratory does not mean the person will carry over and execute those actions outside the clinic, within an unstructured home and community environment. For example, a person can have the strength and coordination to reach and grasp a cup with the paretic UL and demonstrate that capability on a standardized test, but when at home, may (implicitly) choose to reach and grasp cups with the non-paretic limb due to convenience, efficiency, and/or safety [61, 62]. As implicit choices accumulate across activities, hours, and days in the field, the limited activity of the paretic (or both limbs) can be quantified by numerous wearable sensor variables [63–68] that quantify duration, magnitude, variability, and relative limb activity symmetry. If clinical decisions are based only on the measurement of movement in the clinic, rehabilitation clinicians and patients will be missing information needed to address patient goals and improve movement performance in daily life. Wearable sensors,

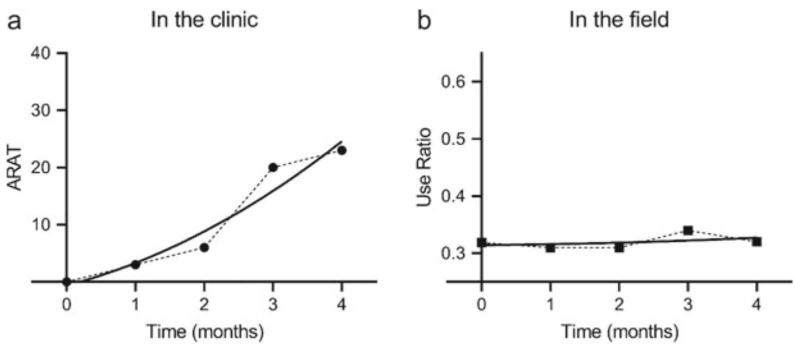

Fig. 21.7 Improvements in in-clinic measures often do not carry over to improvements in the field. Example of an individual receiving outpatient therapy services for the upper limb post stroke. This 47-year-old started outpatient services (time 0) 28 days post stroke, after an inpatient rehabilitation stay. Rehabilitation continued until 5 months post stroke (time 4). Symbols are assessment time points; thick lines represent best fit models. A: Results from in-clinic assessment on the Action Research Arm Test (ARAT, higher = better, 57 = normal). B: Results from monitoring in the field with bilateral, wrist-worn sensors. The use ratio is a ratio of the duration of the paretic limb use to the non-paretic limb use over a 24 h wearing period (higher = better, normative values ~0.9–1.0)

therefore, provide an important opportunity for future improvement of stroke rehabilitation services and stroke rehabilitation outcomes.

21.3.2 Monitoring Upper Limb Movements in the Field

The most common option to measure UL movement is with tri-axial accelerometers. Many commercially available, research-grade devices also contain gyroscopes, magnetometers, inclinometers, and optical sensors. In patient studies, these devices are typically worn on one or both wrists, with monitoring occurring for at least 24 h [69]. Wrist-worn devices capture movements of the upper arm, forearm, and wrist, but not fine dexterous movement of the fingers. Wrist-worn sensors work well for people who are moderately to severely affected post stroke. Wrist-worn sensors quantify UL movement with reasonable accuracy because these individuals cannot make small, fractionated movements of the fingers without moving the wrist, forearm, and/or upper arm [70]. In persons with very mild stroke, where impairments are relatively isolated to dexterous movement of the fingers, then sensors worn on the fingers in addition to the wrist may be needed to better capture UL movement in the field [71].

If one is to monitor UL movement in the field for adequate durations (e.g., 24 or more hours), then the wearable sensors or system of wearable sensors must meet four practical considerations. *First*, being able to monitor both ULs simultaneously is usually necessary, i.e., the sensors need to be worn on both the paretic and non-paretic limbs post stroke. This is because of the enormous heterogeneity in how much/how often humans move throughout a day, but the tight homogeneity in the relative movement of one limb versus the other in neurologically-intact individuals across the lifespan [63, 72, 73]. *Second*, wearable sensors that are on the wrist or fingers need to be waterproof. Humans wash their hands and encounter water during many activities throughout the day. If the sensors have to be removed every time hand-washing is needed, then the likelihood of the sensors being worn and worn correctly decreases substantially. *Third*, straps or pockets that secure the sensors to the UL need to be comfortable and sufficiently easy for a person with stroke to don and doff (alternatively, sufficiently easy for a caregiver to don/doff). Uncomfortable or too tight sensors on the ULs will be removed, while too loose sensors will not accurately track movement. And *fourth*, the fewer number of sensors can be worn on the limb to get the necessary data, the greater the probability they will be worn for the assigned monitoring period. Wearable systems with multiple sensors [74] are feasible for in-clinic measurement, but often will not be worn, worn correctly, or result in loss of the sensors when monitoring in the field. If wearable sensors have an attractive appearance (e.g., a ring looks like a piece of jewelry), then that will further increase wearing compliance. Developing or adapting sensors and sensor systems that adhere to these practical considerations will further the implementation of wearable sensors into routine stroke rehabilitation care.

One of the major challenges to the widespread adoption of wearable sensors in routine stroke rehabilitation care is the lack of clinical validation [68, 75]. The problem is not in the verification of the sensors themselves, but in the clinical validation of the algorithms developed by researchers to derive metrics of clinical relevance. Clinical validation efforts lag behind the engineering development of sensor hardware and software, perhaps because clinical validation is time-consuming, expensive, and requires interdisciplinary teams. Clinical validation is hampered by four key issues. *First*, a large number of variables have been proposed in various research studies, with many different variable names and often different formulae that may be capturing similar or related constructs of movement [68]. *Second*, variables can be mathematically-complex (e.g., Spectral Arc Length as a quantification for UL movement smoothness [76, 77]) and thus hard to interpret clinically with respect to daily activity in the field. *Third*, there are insufficient validation data to indicate which variables carry clinical meaning and are ready to be deployed widely in clinical practice. Most variables have been evaluated in small samples of control or stroke participants at a single point in time. Only a few variables have been evaluated longitudinally in larger samples but lack data on either responsiveness to change and/or how much change is clinically meaningful to patients. One UL variable, the use ratio, is widely used in research and is close to be ready for clinical implementation after being proposed 20 years ago [65]. And *fourth*, UL movement performance in daily life is a complex construct that is likely multidimensional [68, 73, 78]. Thus, there is a high probability that UL movement in the field may be most appropriately represented by multiple variables, not any single variable [79, 80]. For example, the use ratio (Fig. 21.7b) provides information about the relative duration and symmetry of UL movement throughout the day, but other variables could be needed to understand the magnitude and variability. Solving these four issues variable-by-variable for the stroke rehabilitation population will require a large investment of engineering and clinical resources if wearable sensors are to become ubiquitous in UL stroke rehabilitation care.

21.3.3 Monitoring Lower Limb Movements in the Field

Monitoring LL movement in the field shares many of the same benefits and challenges as monitoring UL movement. Unlike the UL, walking is the one essential LL movement activity that rises above all the others. Regaining the ability to walk is the number one goal of most persons undergoing stroke rehabilitation [81, 82]. The primary method to quantify walking performance in the field has been with sensors that count steps/day. Clinicians face a dilemma when trying to use wearable sensors to record steps per day in the field for their patients with stroke. On the one hand, consumer-grade devices worn on the wrist can be inexpensive and are readily available, but can be wildly inaccurate for the majority of persons with stroke who walk slowly, asymmetrically, and/or use assistive devices [83–87]. On the other hand, research-grade sensors are expensive and not easy for clinicians to deploy in a busy clinical environment. A collaborative effort to develop a wearable sensor system that is cost-effective, simple to use, and accurately quantifies walking performance in the field across a broad range of walking abilities will be necessary to make monitoring a routine in clinical stroke rehabilitation practice. Study protocols to capture walking performance typically record behavior for more days (e.g., 5–7 days [88]) than are seen in UL studies [1–3, 69], because of the high amount of variability in daily stepping in persons with stroke [89]. Compliance with wearing tends to decrease over time, especially when people have to wear them at multiple time points [90].

As with UL monitoring, walking performance in daily life may eventually be best represented by multiple variables, not a single variable. Steps/day measures the amount but can miss other aspects such as gait asymmetry, the ability to navigate various environments (e.g., outdoor walking, stairs), and potentially falls. Many of the emerging technologies (see below) could present new opportunities for building multivariate feedback regarding walking. If feedback is provided in a simple, compelling interface for clinicians and persons with stroke, there is a greater likelihood of implementation.

21.3.4 Critical Information Learned from Wearable Sensing in the Field that Would not Be Known Otherwise

While there is much work to be done before wearable sensors and systems are perfected, important knowledge for stroke rehabilitation has already been learned by monitoring movement in the field. Here three examples of new knowledge that could only be obtained from wearable sensing are provided. The first two examples are from samples of persons with stroke wearing bilateral, wrist-worn accelerometers for 24 or more hours, while the third is from persons with a stroke wearing a finger/wrist tracking device for 24 h.

Wearable sensors have challenged assumptions about how persons with stroke maintain the overall amount of UL activity in daily life by compensating with their paretic limb. If the overall amount of activity was maintained, then one would expect a negative correlation between the activity of the paretic limb and the activity of the non-paretic limb (i.e., the paretic limb activity would increase as the non-paretic limb decreased in order to maintain the overall amount of activity). As can be seen in Fig. 21.8, however, there is a strong, positive correlation (r = 0.78, $p < 0.01$) between the duration of use of the paretic versus non-paretic UL post stroke. This positive correlation indicates that as people move the paretic limb less throughout the day, they move the non-paretic limb less too. They are not compensating as much with the non-paretic limb as assumed, but instead doing less activity overall. Interestingly, this relationship is true both early [91] and later after stroke [92]. Stroke rehabilitation clinicians and researchers would not know about the limited UL movement in daily life without monitoring movement in the field with wearable sensors.

Wearable sensors are also changing perceptions about the recovery of UL movement post stroke. Decades of research on recovery trajectories post stroke indicate that larger, rapid changes occur in the first few weeks, with smaller, slower changes occurring later [93–98]. Changes in impairment generally precede changes in functional capacity by around one week, such that as movement control returns, individuals regain the ability to execute functional tasks

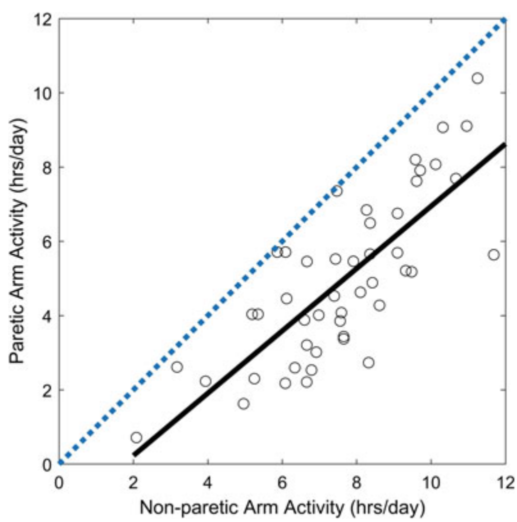

Fig. 21.8 Relationship between movement activity of the paretic (y-axis) vs non-paretic (x-axis) upper limbs in 46 adults with chronic stroke. UL: upper limb. Data from Bailey et al. 2015 (https://doi.org/10.1179/1074935714Z.0000000040)

[96, 97]. The common perception has been that as functional capacity improves in the clinic, then improvements are incorporated into daily life at home and in the community (i.e., activity performance in the field improves). If this perception were correct, one would expect recovery trajectories where a plateau of impairment-level measures occurs first, followed by plateaus in capacity measures, and then finally by plateaus in performance level measures. As can be seen in Fig. 21.9, wearable sensors have discredited that perception [79]. A prospective longitudinal cohort (n = 67) of persons was followed from 2 weeks out to 24 months after first-ever stroke, with bi-weekly measurements of UL impairment (Fugl-Meyer scale [28]), capacity (Action Research Arm test [99]), and performance (use ratio and hours of paretic limb activity [92]). UL performance in daily life (blue line) plateaued surprisingly early after stroke. Plateaus in performance did not lag plateaus in impairment (gray line) and capacity (black line), but instead slightly preceded or occurred at the same time [79]. These data imply that UL movement in the field settles into a stable pattern early and often before neurological and functional recovery is finished. The early plateau in UL performance strongly suggests that to improve stroke rehabilitation outcomes, interventions that pair motor training *and* intentional health behavioral interventions are needed [100, 101].

Finally, wearable sensors have provided new insights into the detailed nature of the relationship between capacity and performance. As discussed in Sect. 21.3.1 and shown in Fig. 21.9, improvements in movement assessed at the capacity level within the clinic often do not translate into improvements in the performance of activities in daily life. Schweighofer et al. [102] hypothesized that real-world UL performance lags clinically-demonstrated UL capacity until UL capacity reaches a threshold; they generated this "Threshold Hypothesis" based on self-reported use of the amount of hand use at home. Data acquired from a novel wearable sensor (called Manumeter) recently confirmed this hypothesis (Fig. 21.10) [103]. The Manumeter consists of a watch-like sensor and a small permanent magnet worn as a ring. The watch-like sensor uses an array of magnetometers to detect changes in the magnetic field as the ring moves due to finger or wrist movement. A total of 29 stroke survivors wore the Manumeter at home during their daily activities for 6–9 h. Capacity

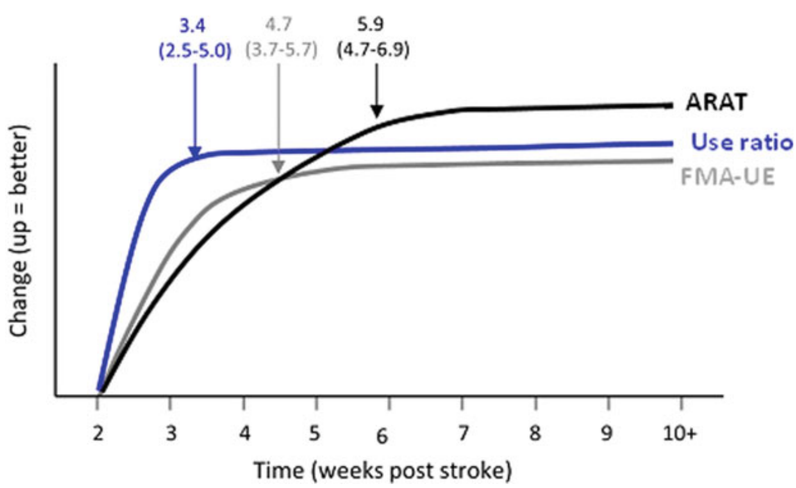

Fig. 21.9 Average trajectories of change over time for impairment (in clinic, gray) capacity (in clinic, black), and performance (in the field, blue). Arrows mark the time of plateau; values are means (95% Cis). Values on the y-axis are theoretical and not intended to be compared across the three trajectories. ARAT: Action Research Arm Test; FMA-UE: Fugl-Meyer Assessment Upper Extremity subsection. Data from Lang et al., 2021 (https://doi.org/10.1177/15459683211041302)

Fig. 21.10 Left: The Manumeter, a device that counts finger/wrist movements by measuring changes in the magnetic field at the wrist sensor produced by the ring. Right: Hand use intensity (i.e., "performance") measured at home for 29 stroke survivors with different levels of hand capacity, as quantified by the Box and Blocks Test (BBT) Score. For the circles, each color represents one subject, and each subject can have one to three samples for up to three different days. Data from Schwerz de Lucena et al. 2021 (https://doi.org/10.3390/s21041502, licensed under CC BY 4.0)

was measured in the laboratory using the Box and Blocks Test (BBT), which requires individuals to pick up and transport as many small blocks as possible in 60 s. Most participants with BBT scores <30 had a low finger/wrist movement count intensity of around 200 counts/h, which is the amount of counts to be expected due to "false positives" from environmental magnetic fields. Then, there was an increase in hand use intensity as participants' BBT scores increased beyond 30, consistent with the Threshold Hypothesis. Thus, achieving a 50% score on a capacity measure predicted the start of use of the hand at home (i.e., increasing performance).

21.4 Wearable Sensors to Motivate Movement and Exercise in the Community

Wearable sensing technologies have proven useful for promoting the activity and health of people without disabilities. For example, a 2007 systematic review in JAMA found that daily pedometer feedback is an effective way to increase walking activity and thereby improve difficult-to-change health outcomes such as body mass index and blood pressure [104]. Recognizing this finding, many companies now sell wearable sensors and phone apps for counting steps. The global fitness tracker market is projected to grow from $36.34 billion in 2020–$114.36 billion in 2028 [105].

Goal setting with feedback is known to be a powerful modulator of performance [106] and indeed it appears to be a key requirement for the successful use of such fitness trackers. Based on an analysis in the systematic review of pedometer feedback referred to above, setting a step goal (e.g., 10,000 steps) was significantly associated with an equivalent one-mile increase in steps/day, while individuals who did not set a goal did not significantly increase their step count. In the context of rehabilitation, a seminal multisite randomized controlled trial on the use of quantitative performance feedback, the SIRROWS study, showed that providing individuals post stroke with their completion time in a 10 MWT at regular intervals throughout rehabilitation therapy, along with a simple comment on whether that time exceeded their previous time, significantly improved their gait speed over the course of therapy compared to individuals who did not receive this feedback [107]. Presumably, the quantitative feedback caused patients to set a goal of improving their gait speed at the next test. Goal setting is thought to affect performance through four mechanisms: (1) directing attention toward goal-relevant activities and away from goal-irrelevant activities; (2) energizing greater effort; (3) increasing persistence; and (4) stimulating arousal, discovery, and use of relevant strategies [106], all of which could play a role in rehabilitation.

When considering the motivation for applying wearable sensing in rehabilitation practice, a key issue is increasing amounts of movement practice. While rehabilitation research has not yet been able to precisely define sufficient, patient-specific goals for the amount of practice in a scientific way, there is a broad consensus that patients typically do not practice enough. In-clinic therapy sessions achieve a limited number of practice repetitions [108], and health payors limit the number of reimbursed therapy sessions. Therapists, therefore, create home exercise programs to increase rehabilitation doses. Yet adherence to home programs is low, even if the prescribed exercise program is unambitious [109–111]. Further, as reviewed above, the amount of use of an impaired limb in daily life is often low, even for people with substantial functional capacity. Low daily use of a limb is thought to create a “vicious cycle”, contributing to further degradation of movement ability [102]. Thus, a primary goal for wearable sensing after stroke is to create a “virtuous cycle”, in which patients move more frequently, whether during exercise sessions or during daily life, in order to promote movement recovery.

21.4.1 Promoting Upper Limb (UL) Movement

Despite the availability of a clear pragmatic goal (i.e., facilitating more movement practice), few wearable sensing studies have attempted to achieve this goal [27]. Initial studies suggest that increasing movement is possible, but likely requires goal setting and coaching along with wearable feedback. Delivering improved UL outcomes may also be possible but may be more difficult than what might have been expected given the pedometer literature.

21.4.1.1 Providing Feedback on UL Movement Amount

Whitford et al. [112] were among the first to study the use of wearable sensors to generate feedback about UL use in stroke survivors. In their study, eight chronic stroke survivors wore accelerometers without feedback screens on both wrists during waking hours for three weeks. Research therapists visited their homes three times per week to collect and process data. They provided feedback on the amount of activity and disparity of activity between arms through verbal discussion and by presenting graphs. At each of these feedback sessions, participants also set two goals related to increasing their paretic UL activity. Their therapist reviewed progress toward these goals with them at the next session. This strategy significantly increased participants’ perception of paretic UL activity. Yet no improvements in actual activity of the UL (as measured using the accelerometers) or in functional outcomes were found.

Another recent study provided feedback on the number of wrist and finger movements made throughout the day to try to motivate increased UL use [113]. Twenty chronic stroke participants wore the Manumeter, the wristwatch-like device described above that senses the magnetic field of a small magnet ring worn on the index finger, using a nonlinear detection algorithm to calculate the number of finger movements [103]. Participants in the experimental group received real-time feedback on finger movement counts and a daily goal personalized to their impairment level. Subjects in the control group used the device as a wristwatch, but the device still tracked the number of finger movements. Both groups also were given a home exercise program described in a booklet. After data analysis, it was found that the experimental group chose to wear the Manumeter for approximately one hour more each day, but did not increase their finger movement intensity, measured as counts per hour. Scores on the BBT and MAL did not improve significantly at 3 months, although scores on the FMA-UE and the ARAT improved for both groups.

21.4.1.2 Reminders to Move

A different approach is to use a wearable device to provide reminders (or "nudges") to move the limb, usually in the form of vibrations [18]. In this case, the device can provide the nudge after sensing a period of relative inactivity, or, alternately, the device need not necessarily sense limb movement, but instead can provide reminders based on a timer, similar to a water intake management app. Three pilot studies have shown the feasibility of this approach. Signal et al. [114] studied via an observational methodology conducted when stroke patients were inpatients whether "haptic nudges" caused an increase in probability of moving their arm. They used a Bluetooth-enabled wearable device to provide three consecutive vibratory stimuli of 0.3 s duration at 150 Hz within 1.5 s, with a magnitude similar to a phone vibration. Patients were instructed to "move, try and move, or visualize moving their (affected) arm" following a nudge. Observers discreetly followed stroke inpatients out of their field of view, logging UL movement for one minute every 10 min. They randomly delivered haptic nudges or no intervention just before the observation periods. The odds ratio of moving the UL following a haptic nudge relative to no nudge was 1.44, demonstrating an increase in UL activity in response to the haptic nudge.

A second feasibility study used an acceleration-sensing wristband with seven stroke patients ≤ 28 days post stroke for four weeks [115]. Therapists reviewed movement activity data twice weekly with their patients. The wristband was programmed with a personalized threshold for providing a vibratory prompt (5, 25 or 50% greater than the median activity). Mean activity increased in the hour following a prompt (by 11–29%) compared to the previous hour, as measured by the accelerometer in the wristband. 96% of patients expressed a preference that reminders be delivered once per hour, rather than 2, 3, or 4 times per hour. 75% of patients expressed a preference that the target threshold for triggering vibration be set at the lowest setting (i.e., 5% above the previous median baseline activity). In a follow-up pilot study [116], the same research group studied 33 patients 0–3 months after stroke receiving a four-week, self-directed therapy program with a twice-weekly therapy review. The wristband adjusted the threshold and frequency of delivery of the vibration prompt based on the activity level of the wearer. The wristbands were worn for 79% of the recommended time (between 8 AM and 8 PM). Patients again showed a preference for hourly prompts and not more frequent prompts. While clinical outcome measures were acquired, no statistical comparisons were made with a control group in this pilot feasibility study.

In terms of the therapeutic efficacy of this reminder approach, a vibration-based, remind-to-move sensor was tested in a study with 84 stroke survivors who had the first stroke in the last six months [117]. Participants were randomly allocated to either an experimental group (device worn with vibrations delivered), sham group (device worn with no vibrations), or control group (usual therapy). The patients wore the wrist vibrator for three consecutive hours daily over four weeks. The device emitted a vibration cue similar to the vibration mode of a mobile phone every 10 min. The vibration would not stop until a button on the device was pressed. A small but statistically significant greater improvement in one of the clinical outcomes (the ARAT) was observed. A significant difference in the amount of arm activity between groups (measured by an accelerometer embedded in the wristband) was also observed.

These studies suggest that providing movement reminders through vibratory inputs can increase the amount of UL activity and that this increase may have at least a small therapeutic benefit.

21.4.1.3 Providing Feedback on Exercise Activities

Wearable sensors can also be used to provide users with feedback as they perform exercise activities at home. In this case, other types of non-worn sensors, such as camera-based systems or instrumented objects, can serve similar functions. There is a large and growing literature on clinical trials conducted with a variety of sensor-based exercise systems, and numerous commercial systems are available. Here, we briefly review two important studies that focused on using wearable sensors to provide feedback on exercise activities.

A key concern of rehabilitation therapists in providing home exercise is their inability to provide real-time feedback on the quality of the exercise. Performing poor quality exercise is thought by some to be suboptimal or even detrimental to recovery. Wearable sensors have shown potential to help solve this problem. Lee et al. asked 20 people with stroke to wear IMUs on each wrist as they performed assessments and participated in UL therapy [18]. Using video analysis as the gold standard, they showed that they could distinguish goal-directed movements (such as participating in an UL assessment, ADLs, or therapy) from non-goal-directed movements (such as arm swing, gesturing, and resting periods) with an accuracy of 87%. During the performance of a particular exercise ("arm raise in the sagittal and coronal planes"), they could identify when the therapist provided corrective feedback with an accuracy of 84%.

Chae et al. used a wrist-worn sensor to detect when individuals with chronic stroke were performing UL exercise at home [118]. They assigned patients four UL exercises (Bilateral Flexion, Wall Push, Active Scapula, and Towel Slide). Based on in-clinic data, they showed that they could identify the type of exercise from this small set with up to 98% accuracy. The system also recorded exercise repetition counts and duration of exercise, reporting it via an app to a supervising therapist who then contacted the patients once a week to review their progress. A control group received the exercise program on paper without a sensor and was also contacted once a week. A total of 38 participants were enrolled. All participants in the control group had dropped out after 18 weeks, while 12 of 22 in the wearable sensor group persevered to the end. They observed improvements in the WMFT and range of motion of shoulder flexion and internal rotation in the sensor group, while the control group showed only a significant change in shoulder internal rotation.

These studies outline the potential for wearable sensors to provide movement quality feedback, and to serve as a motivational aid by giving therapists a "window" into their patients' home exercise adherence.

21.4.2 Providing Feedback on Lower Limb (LL) Movement Amount

Research progress with wearable sensors for encouraging walking after stroke is more developed than research to encourage UL activity. A 2018 Cochrane review examined the available evidence regarding the effectiveness of wearable sensors (such as pedometers, Fitbit, and Garmin watches) as well as smartphone activity monitors for increasing physical activity levels for people with stroke [119]. This review found four studies that met its criteria with a total of 245 participants in the subacute or chronic phase post stroke. All studies compared the use of an activity monitor plus another rehabilitation intervention that was focused on walking versus the other intervention alone. The review found no clear effect of the use of activity monitors on step count in a community setting or in an inpatient rehabilitation setting.

More studies have been published since this review with mixed results. Mandigout et al. studied 83 participants at an average time of 2.4 months after stroke [120]. Participants were randomly assigned to receive individualized coaching or standard care for six months. The coaches monitored physical activity with an activity tracker (SenseWear Armband) and conducted home visits and made a weekly phone call to review activity. The difference between the two groups was not significant at any evaluation time point for the primary endpoint, the 6 MWT.

On the other hand, Montserrat randomized 41 chronic stroke survivors to a conventional rehabilitation program or to a Multimodal Rehabilitation Program that monitored adherence to physical activity [121]. The multimodal program combined an app with GPS and accelerometer-based sensing to monitor walking distance and speed, a pedometer, a WhatsApp group, an exercise program with aerobic, task-oriented, balance, and stretching components, and a progressive daily ambulation program that was monitored by the app and pedometer. At the end of the intervention, community ambulation increased more in the intervention group (38.95 vs. 9.47 min), and sitting time decreased more in the intervention group (by 3 vs. 0.5 h/day).

Although it focused on a broader population than just stroke patients, a recent pragmatic clinical trial of 300 mobility-impaired patients (including stroke patients) likewise found a benefit from a multimodal program incorporating digital technology [122]. A physical therapist individually prescribed technology that included virtual reality video games, activity monitors, and handheld computing devices. The technology was used for six months in the hospital and at home; patients used on average four technologies in the hospital and two at home. The most commonly used digital technology in the home was a wearable activity monitor (Fitbit or Garmin, used by 98%), followed by an iPad exercise app (used by 86%). Changes in mobility scores (measured by the performance-based Short Physical Performance Battery) were about 10% higher in the intervention group compared to the control group ($p = 0.006$). However, there was no evidence of a difference between groups for an upright time at 6 months.

21.4.3 Summary

In summary, the promise of using wearable sensors to encourage UL and LL activity in the community after stroke has not yet been realized. For the UL, at this early stage of research, the reminder paradigm has perhaps shown more potential for increasing activity and reducing impairment than the paradigm of goal setting with performance feedback from a wearable sensor. For the LL, recent studies suggest that programs that incorporate wearable sensors into multimodal therapy programs may be more effective at increasing walking activity than programs that focus on goal setting with performance feedback alone. We suggest that optimizing the programmatic context in which wearable feedback is delivered will be important for realizing the potential of this technology, and will likely include intentional health behavioral interventions, as suggested above. Key factors to consider are the way goals are set, the specific form of the performance feedback (including both quantity and quality feedback), the availability and nature of therapist coaching, and the integration of a diversity of therapeutic activities along with the wearable feedback.

21.5 Emerging Technologies and Their Potential Applications

The previous sections of this chapter have provided an overview of prior work focused on facilitating the implementation of rehabilitation interventions and the assessment of clinical outcomes by relying on wearable sensors consisting of "units" (often relying on wireless technology) that are typically attached to body segments using elastic straps (e.g., wristbands). In this section, we will consider other technologies. Recent advances in e-textiles and materials science have allowed researchers to explore the use of garments with embedded sensors as well as the development of sensors that conform to the anatomy in a way that is similar to an adhesive bandage (often referred to as e-skin sensors). Furthermore, because contextual information is often essential to perform a meaningful analysis of movement patterns, researchers have begun to explore the use of wearable cameras to gather such information. Radio tags and radar-like technologies could be utilized to gather contextual information, but their use has so far received little consideration in the field of rehabilitation. Recent advances in video analysis techniques, largely enabled by the development of deep learning-based algorithms, have generated significant interest among rehabilitation specialists. These techniques provide an unprecedented capability to track movement patterns with low-cost cameras and are likely to replace the use of wearable sensors in systems designed for home-based rehabilitation. Finally, existing and emerging wearable, as well as contactless technologies, provide researchers and clinicians with the ability to monitor the physiology of patients in the home and community settings. Although a thorough discussion of their potential applications to stroke rehabilitation is beyond the scope of this chapter, in this section, we briefly mention a few examples.

21.5.1 E-textiles

E-textiles are fabrics designed to enable embedding electronics in objects and garments, thus allowing researchers and clinicians to monitor patients outside of the laboratory. A recent review by Angelucci et al. [123] provides a summary of the methods (e.g., coating and printing) traditionally used to make conductive yarns and then use them to make e-textile garments by relying on techniques such as knitting, weaving, and embroidery. The development of e-textile systems for patient monitoring was originally motivated by the assumption that providing patients with garments equipped with sensors would have resulted in better compliance than the use of wireless sensors to be strapped to body segments.

The first steps toward developing e-textile systems were marked by major contributions by Jayaraman et al. [124–126] and by De Rossi et al. [127–129]. Seminal work by Jayaraman et al. [124–126] resulted in the development of conductive yarns enabling the connection of sensors embedded in the garment to a data logging unit, hence allowing researchers to monitor patients' physiology. Shortly after the publication of this work, De Rossi et al. [127–129] introduced the use of conductive polymers to print strain sensors on lycra garments. This work was particularly focused on monitoring movement patterns in individuals undergoing rehabilitation. Following their initial work with a focus on developing e-textile garments, De Rossi and colleagues implemented a fully-functioning platform to monitor stroke survivors and facilitate the performance of rehabilitation exercises [130].

Unfortunately, technical limitations marked these initial prototype e-textile systems. Researchers found it challenging to develop e-textile garments that could be washed multiple times without being damaged. Besides, components such as the connectors between the conductive elements of the garment and the traditional electronics (e.g., data logging units) to be used with the garment turned out to be difficult to manufacture in a way that met the technical specifications of the problem at hand. Nonetheless, this seminal work generated a great deal of interest in the application of e-textiles in the rehabilitation of patients with neurological conditions, including stroke, as summarized in a review paper by McLaren et al. [131]. Interestingly, this review devoted significant attention to e-textile gloves and socks [132]. These are interesting technologies, though e-textile gloves have been found by many researchers to be of limited use in stroke survivors, because these patients have difficulties donning and doffing gloves, particularly on their stroke-affected hand. Similarly, e-textile socks have been seldom utilized in clinical studies, as researchers have often found it more practical to use instrumented insoles to collect proxy measures of ground reaction forces.

New approaches to the development of e-textile garments are currently emerging that appear to have addressed the main limitations of previously developed prototype systems. An example of the techniques used in recently developed e-textile systems is shown in Fig. 21.11. These e-textile garments are based on embedding flexible electronics in pocket-like components typically referred to as "textile channels". The use of traditional integrated circuits allows researchers to take advantage of advances in sensing technology. New materials are used to encapsulate electronic components, thus making them washable and mechanically robust.

It remains to be seen if these new approaches to the development of e-textile garments can

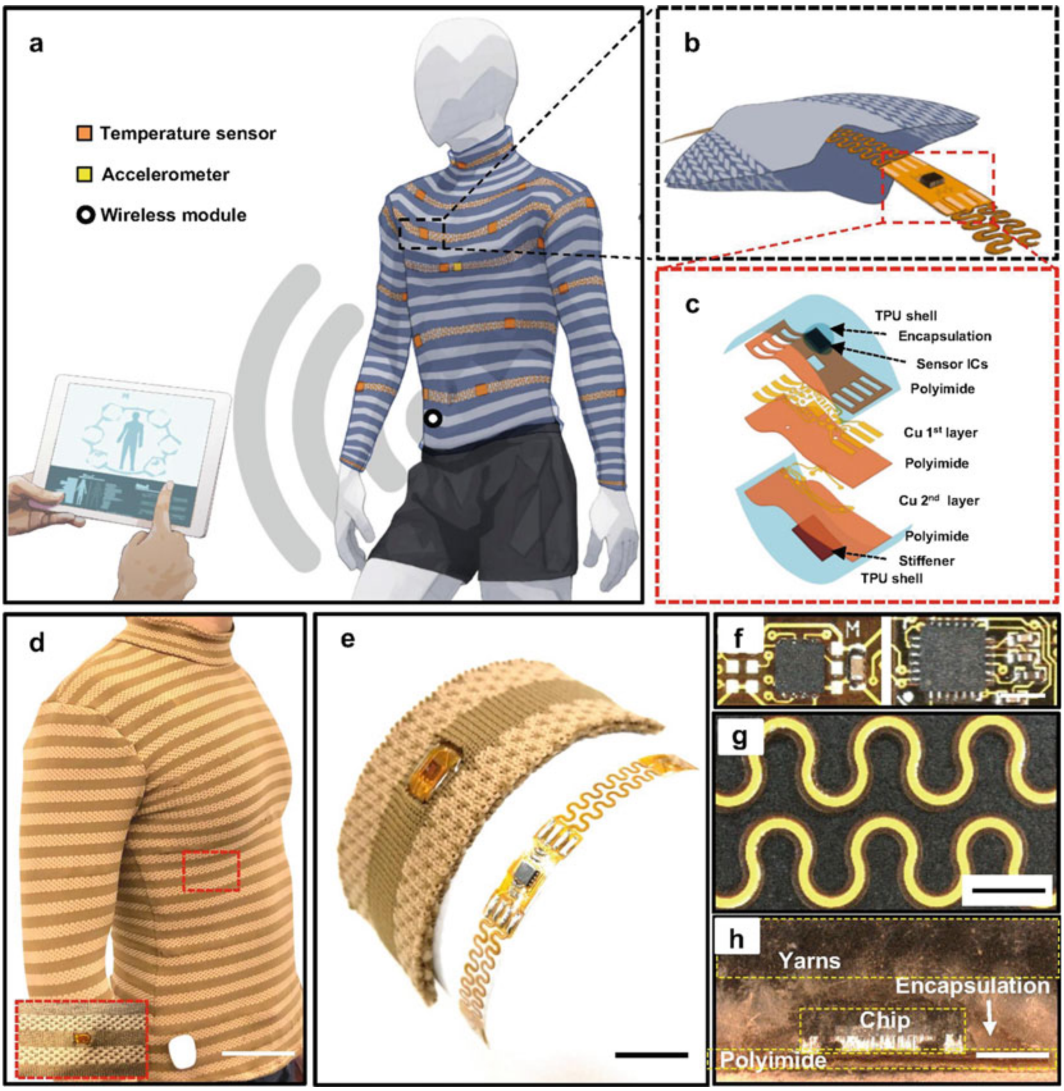

Fig. 21.11 Recent implementations of e-textile garments rely on deploying multiple sensors (panel a) embedded using pocket-like textile channels (panel b) containing sensor islands (panel c) equipped with traditional integrated circuits on a flexible substrate (made of copper and polyimide layers) covered by thermoplastic polyurethane (TPU) and a washable encapsulant. The garment, shown in panel d (scale bar: 10 cm), carries flexible-stretchable electronic strips (right) and woven electronic strips in a knit textile (left) as per the example shown in panel e (scale bar: 1 cm). Examples of temperature and accelerometer integrated circuits are shown in panel f (scale bar: 3 mm). Panel g shows an example of an interconnect module (scale bar: 2 mm). Panel h shows a cross-sectional view of a sensor module embedded in a polydimethylsiloxane (PDMS) layer (scale bar: 2 mm). Reproduced with permission from Wicaksono et al. (https://doi.org/10.1038/s41528-020-0068-y, licensed under CC BY 4.0)

deliver on the promise to achieve higher compliance than wearable sensors that are strapped to body segments. That said, the use of e-textile garments is appealing in clinical applications requiring long-term monitoring as one would anticipate that patients would prefer wearing a garment with embedded sensors rather than having to don and doff multiple elastic straps equipped with sensing technology every day during the monitoring period. Similarly, one would anticipate that patients required to perform vigorous motor activities (e.g., aerobic exercises) would prefer wearing an e-textile garment rather than elastic straps equipped with sensors because elastic straps would be more likely to interfere with the movements to be performed and migrate during the performance of motor tasks.

21.5.2 E-Skin Sensors

The development of stretchable electronics matching the mechanical characteristics of the epidermis, which was pioneered by John Rogers' research group [133, 134], enabled the development of e-skin sensors. These are sensors that, when attached to the skin like an adhesive bandage, stretch in the same way as the skin does in response to the movement of body segments. This technology has recently led to the implementation of movement tracking systems like the one schematically represented in Fig. 21.12. This figure shows recent work by Kim et al. [135] aimed to detect and estimate the characteristics of movements involving different body segments (panel a) from data collected by relying on e-skin sensors positioned on specific body landmarks. The e-skin sensors allow one to capture skin topographical changes associated with the target movement. For instance, movements of the index finger are detected, and their biomechanical characteristics are estimated using an e-skin sensor positioned at the wrist (panel b of Fig. 21.12). High sensitivity to the movements of the index finger is achieved by relying on laser-induced nanoscale cracking—shown in the inset of panel b (scale bar: 40 μm)—of specific elements of the mesh displayed in panel c (scale bar: 1 mm). Advanced data analysis techniques that rely on deep neural networks are used to estimate the biomechanical characteristics of the index finger movements.

As the technology rapidly evolves and major advances in the field of flexible and printed

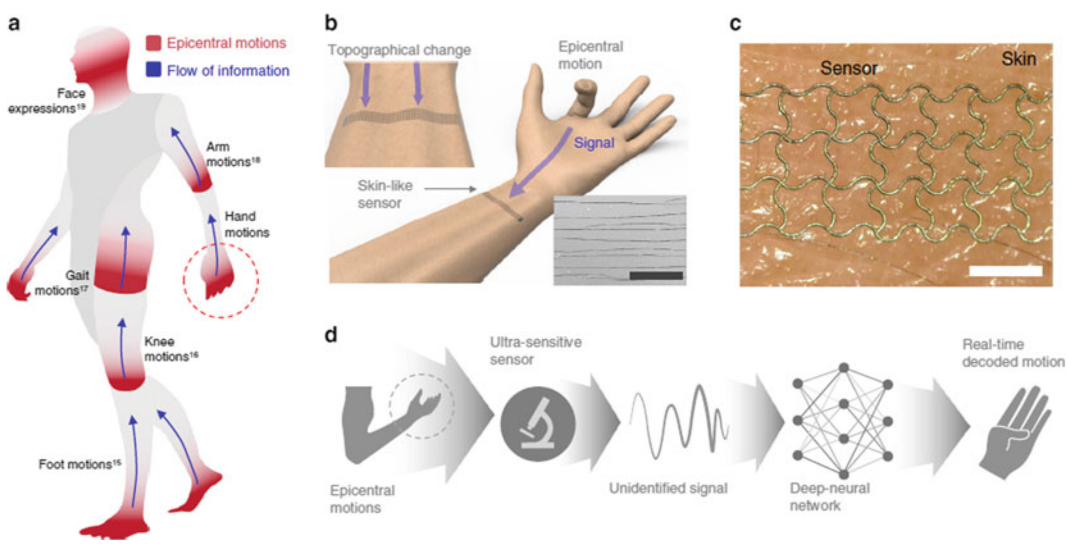

Fig. 21.12 E-skin sensors can be used to monitor movements involving different body segments (panel a). The sensors are positioned on specific anatomical landmarks (panel b) with laser-induced cracking (panel b inset) affecting specific elements of the mesh structure (panel c) used to build the sensor. Data collected using the sensor is processed by deep neural networks (panel d) that generate estimates of the biomechanical characteristics of the movement performed with the monitored body segment. Reproduced with permission from Kim et al. (https://doi.org/10.1038/s41467-020-16040-y, licensed under CC BY 4.0)

electronics are expected over the next few years [136], the interest in potential clinical applications of e-skin sensors, including stroke rehabilitation, is rapidly growing [137]. E-skin sensors are expected not only to facilitate tracking the movement of body segments, but also to enable the detection of the activity of muscles either by electrode arrays mounted on a flexible substrate or by detecting changes in the shape of body segments associated with the contraction of muscles.

The use of e-skin sensors is very appealing for short-term (i.e., a few days) monitoring of motor activities in stroke survivors. When used for longer periods of time, e-skin sensors are likely to cause skin irritation as adhesive components are typically used to secure the sensors to the skin and such materials tend to cause skin irritation when utilized over long periods of time. Nonetheless, e-skin sensors are marked by minimum obtrusiveness and optimal wearability. Hence, a growing interest in this technology is expected over the next years.

21.5.3 Wearable Cameras

The use of wearable cameras (Fig. 21.13, left panel) in the field of rehabilitation was originally proposed to validate the detection of motor activities achieved via the analysis of wearable sensor data and provide contextual information. The manuscripts by Doherty et al. [138] and by Lee et al. [71] are examples of this body of work that relied on egocentric video recordings (i.e., recordings that approximate the visual field of the camera wearer) to capture the environmental conditions in which tasks were performed and hence infer the nature of the tasks. Ad-hoc techniques to analyze egocentric video recordings were developed to facilitate the identification of the environment where motor tasks were performed and the conditions in which they were performed. These techniques allowed researchers to minimize the need to manually annotate lengthy recordings. The manuscript by Yan et al. [139] provides an example of such video analysis techniques.

Wearable cameras have also been used to replace wearable sensors. Seminal work by Zariffa and Popovic [140] explored this application of wearable cameras nearly a decade ago. Subsequently, the research group led by Jose Zariffa further developed this technique in a series of studies carried out first in individuals with spinal cord injury and later in stroke survivors. The right panel of Fig. 21.13 shows examples of the motor tasks analyzed via recordings collected using a wearable camera [141]. In this specific project, the research team used a convolutional neural network to detect the position of the hands in the video frames and used a Random Forest-based classifier to detect when subjects manipulated objects. Subsequent work by the same group explored the combined use of object detectors and trackers [142] as well as the detection of compensatory movement strategies adopted by patients with UL motor impairments [143].

This body of work was focused on the application of wearable cameras to detect and assess the quality of UL movements in individuals with spinal cord injury. Whereas initial work was carried out in the laboratory, recent studies have explored the use of this technology in the field [144]. Importantly in the context of this book chapter, the same research group has started to explore the use of this technology to monitor UL movements performed by stroke survivors [145]. The authors were able to demonstrate the feasibility of tracking hand use and determining if the stroke-affected hand was utilized for the stabilization or the manipulation of objects.

Researchers can now rely on a large body of work focused on the development of techniques for the analysis of egocentric video recordings. Studies relevant to the application of wearable cameras in the field of rehabilitation were recently reviewed by Bandini and Zariffa [146]. The authors surveyed techniques designed to identify the hands or parts of them in the video frames and to detect the task performed by the camera wearer. They also provided a summary of the various applications of these techniques that are currently pursued by researchers, including remote assessment of hand function and gesture recognition. Novel video analysis techniques are

Fig. 21.13 A wearable camera (left panel) can be utilized as an alternative to wearable sensors to detect UL motor activities (right panel). Reproduced with permission (Vicon Revue camera picture courtesy of Oxford Metrics, UK—left panel; Likitlersuang et al. (https://doi.org/10.1186/s12984-019-0557-1, licensed under CC BY 4.0)—right panel)

emerging that are expected to further facilitate the analysis of egocentric video recordings by addressing challenges such as those associated with the continuous change in visual field due the movements of the body segment the wearable camera is attached to [147].

Future developments in this research area are expected to focus on more complex analyses of the contextual information gathered using wearable cameras. For instance, the identification of objects in the video frames could determine the degree of hand dexterity required for their manipulation, which, in turn, could provide a reference to evaluate if the movements of the stroke-affected hand are adequate to meet the task requirements. Furthermore, the development of techniques for quasi-real-time analysis of video recordings gathered using wearable cameras could provide an opportunity to generate stimuli to encourage the use of the stroke-affected hand. Techniques previously developed using wearable sensors positioned bilaterally at the wrist to detect UL activities and deliver stimuli to encourage stroke survivors to use their stroke-affected arm [18] have been shown to be effective in pilot clinical studies (unpublished results). Systems relying on wearable cameras could provide additional information suitable to choose the timing of the stimuli delivered to remind stroke survivors to use their stroke-affected limb in a way that is most likely to lead to a positive behavioral change. For instance, stimuli could be delivered when the patient is engaged in a task that has been identified by the patient—in consultation with the therapist—as a task suitable to increase the use of the stroke-affected arm.

21.5.4 Radio Tags and Radar-Like Technologies to Gather Contextual Information

Whereas the use of wearable cameras could provide useful contextual information, privacy concerns are likely to limit their use and encourage researchers to seek alternative approaches. In a controlled environment (such as the home), systems relying on radio tags and radar-like technologies provide an interesting alternative to the use of wearable cameras. Whereas a review of these technologies is beyond the scope of this chapter, it is important to point out that significant advances have been achieved toward providing accurate data about the position in the home environment of people and objects using a variety of techniques. Herein, we have chosen to briefly comment on the use of ultra-wideband (UWB) radio systems [148] and radar-like technologies [149] as we believe that these techniques are particularly promising.

The localization of UWB radio tags is a well-studied problem. Capra et al. [148] explored the use of this technology to track the position of patients in the home environment and provide immediate assistance when a fall is detected using a wearable sensor connected to the UWB network. Localization algorithms relying on UWB radio tags use sets of transceivers with a minimum of three units utilized as anchor points (i.e., units set in known positions) that serve as a reference to locate radio tags in the environment. Radio signals are exchanged among the anchor point units and the radio tags. Estimates of the time of flight (i.e., the time needed to receive a radio signal) for different anchor points are used as input to a triangulation algorithm that determines the position of the radio tags relative to the anchor point units. Recent advances in UWB technology include the development of methods for self-calibration of the position of anchor point units [150], thus making the deployment of UWB localization systems both simple and inexpensive.

UWB localization systems can be looked upon as part of a broad category of systems including those that rely on Internet of Things (IoT) and radio frequency identification (RFID) technologies, which are becoming common place and provide the opportunity to track the position of people and objects in the home environment as reviewed by Landaluce et al. [151]. Besides, researchers have developed several techniques to take advantage of and merge the information gathered in the environment using different wireless technologies in ways that are suitable for tracking purpose [152]. Researchers are beginning to envision tracking stroke survivors as they move from room to room in the home environment (e.g., they move to the kitchen at lunchtime) and detect their proximity to objects (e.g., a cutting board on the kitchen counter) that enable inferring that they are engaged in specific activities (e.g., preparing a meal). This contextual information could be utilized to analyze sensor data accounting for the activity that stroke survivors are engaged in. Also, contextual information could be used to generate stimuli to encourage patients to use their stroke-affected arm to perform specific activities.

Radar-like systems [153, 154] designed for deployment in the home setting [155] are rapidly emerging as ideally suited to track people's location. Seminal work by Dina Katabi's group [153, 154] relies on the analysis of how radio signals bounce off the body to track the position of people in the home environment. Figure 21.14 shows a prototype system developed by Dina Katabi's research team at MIT (left panel) and a graphical representation of the radio signals that bounce off the body of the study volunteer as he walks in the room (right panel). The technique developed by this research team can achieve an accuracy of 10–20 cm, which is generally satisfactory in the context of the above-mentioned applications. Among all available technologies for position tracking, this appears to be the most promising. It does not require anything else than positioning in the home a box similar to a WiFi router. Importantly, it does not require that patients wear sensors or radio tags and it does not require a complicated installation. Current implementations are challenged when tracking people in crowded environments. However, that is a situation that seldom occurs in the home of stroke survivors, where typically the system would need to track a few individuals at the most.

21.5.5 Modern Video Analysis Techniques

The development of advanced machine learning techniques that has taken place over the past decade has led to a new generation of video analysis techniques that are dramatically transforming the field of movement science. A number of sophisticated software libraries have been made available to the scientific community including DeepPose [156], DeeperCut [157], OpenPose [158, 159], ArtTrack [160], DeepLabCut [161], Alpha-Pose [162], and MediaPipe [163–165]. These software libraries rely on deep learning algorithms designed to track anatomical landmarks (referred to as "keypoints")—such as the ankle, knee, and hip joint positions—and derive a simplified representation of the body as shown in Fig. 21.15a. This process is referred to as "pose estimation" and can be implemented by using low-cost video cameras. Although the results are not as accurate as those obtained by using traditional, high-cost, camera-based motion capture systems, these modern video analysis techniques provide a valid low-cost alternative when the application at hand does not have stringent accuracy requirements. It turns out that this is the case for many clinical applications such as the assessment of motor patterns to estimate the severity of motor impairments and the generation of feedback during the performance of rehabilitation exercises (e.g., to detect and discourage compensatory movement strategies).

The above-stated considerations have generated tremendous interest among researchers and clinicians for these techniques. Recent reviews have discussed their potential impact on clinical practice [166–168]. However, clinical adoption is still limited. A large number of studies have been focused on the technical validation of these techniques, especially in the analysis of gait patterns [169–172]. Recent publications have started to discuss the possibility of using these techniques to derive proxies for clinical assessment measures [173, 174]. A few studies have explored

Fig. 21.14 Radar-like systems can provide a totally unobtrusive way to monitor patients' position in the home environment and hence infer contextual information of great use in home-based interventions. The sensor (left panel) consists of a radio transmitter/receiver array. The radio transmission bounces off the person, for instance, while walking and result in a "radio signature" (right panel) from which the position of the patient can be inferred with a 10–20 cm accuracy. Reproduced with permission from Prof Katabi's webpage

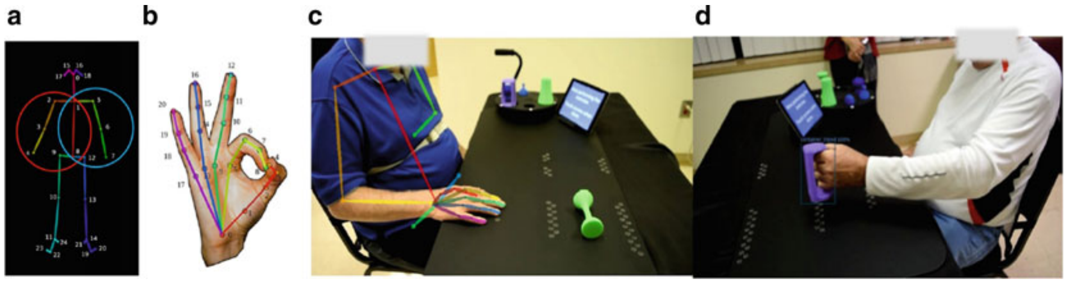

Fig. 21.15 Output of the OpenPose algorithm used to generate a stick figure representation of the patient (**a**). Keypoints used to track hand movements (**b**). Stick figure representation derived using OpenPose overlaid to a video frame (**c**). Output of the algorithm used to track objects (**d**). Reproduced with permission from Ahmed et al.

their use for tracking UL and hand movements [175, 176]. The manuscript by Ahmed et al. is particularly interesting as it explores an important application of modern video analysis techniques, namely tracking movement during the performance of home-based rehabilitation exercises. The manuscript provides details about the work accomplished toward the development of a platform for UL home-based exercises named the Semi-Automated Rehabilitation at the Home (SARAH) system. Figure 21.15 shows some of the key components of the system: the stick figure representation of the body obtained using OpenPose [158, 159] (panel A), the keypoints used to track hand movements (panel B), the OpenPose stick figure representation overlaid on a video frame (panel C), and the output of the object tracking and recognition algorithm used in the study (panel D) [177].

21.5.6 Collecting Non-motor Data

Although this chapter is devoted to movement tracking-based techniques, wearable sensors can provide additional information that is relevant to stroke rehabilitation. For instance, wearable sensors provide a convenient way to monitor systemic responses associated with vigorous exercise, which should be monitored in stroke survivors [178]. The use of wearable sensors and systems in this context is becoming common place in clinical studies [179] and adoption in the clinic is ramping up. Additional applications of wearable technology are emerging. For instance, commercially available wearable systems provide a convenient, unobtrusive way to monitor sleep quality. An example of a sleep report generated by a finger-worn wearable sensor is shown in Fig. 21.16. Sleep quality is important not only as a proxy for wellness and psychological status, but also in the context of motor learning. In fact, motor learning studies have pointed out the important role played by sleep in the processes associated with the consolidation of learned motor patterns [180].

In the future, we envision that metrics of this type will be used routinely in clinical care. However, clinical studies are needed to develop reliable metrics that could inform the design of personalized (i.e., patient-specific) interventions that account for multiple physiological factors and the general well-being of patients.

21.5.7 What Emerging Technologies Could Do that "Traditional" Technologies Do not …

E-textiles provide an alternative form factor that patients might prefer over traditional wearable systems for long-term monitoring applications. Traditional wearable sensors are typically

Fig. 21.16 Subject wearing a commercially available ring sensor (right, picture from Oura Health Oy) that provides measures of sleep quality via the companion smartphone application (left). Sleep quality is relevant to stroke rehabilitation in many ways, including the impact on the consolidation of motor gains

attached to the body via elastic straps. When multiple sensors have to be used for a long period of time on a daily basis, they are rapidly perceived by patients as obtrusive. In contrast, an e-textile t-shirt could be used to embed multiple sensors and require donning and doffing a single item.

Nonetheless, e-textiles cannot always conform perfectly to the anatomy and often do not provide a stable contact between the sensing elements and the patient's skin. In these circumstances, researchers can rely on e-skin sensing technology. The quality of the contact with the skin achieved using e-skin sensors is unprecedented. In these specific applications, e-skin sensors deliver high-quality data that would be difficult to achieve with traditional wearable sensing technology as well as with e-textiles.

When the analysis of data collected using wearable sensors requires contextual information, one can rely on wearable cameras to collect egocentric video recordings. Patients would wear traditional sensors or e-textiles or an e-skin sensor or a combination of all of the above. The egocentric video recordings would provide context and hence facilitate the analysis of the data. However, this approach clearly presents privacy concerns.

When one needs to monitor patients in the home environment, then wearable cameras can be replaced by other technologies such as radio tags and radar-like technology solutions. Whereas further research is needed to develop and test contactless technologies—like the ones mentioned above—to track patients in the home setting with high accuracy, existing radio tag systems and radar-like technology solutions provide sufficient accuracy to enable inferring important contextual information.

Researchers and the rehabilitation technology industry have relied on wearable sensors to generate feedback during the performance of therapeutic exercises (whether in the clinic or at home). The use of modern video analysis techniques is now replacing traditional sensors in this context. In fact, the use of video analysis technology is more convenient as it does not require any donning and doffing of sensor units, which is often problematic for stroke survivors. A preference for video analysis solutions would be expected when one implements rehabilitation interventions using interactive games. This solution would be less attractive when clinicians would like to monitor rehabilitation in an inpatient gym, where a large number of patients would like to be present at the same time.

Finally, it should be emphasized that "traditional" consumer electronics provide data that is highly relevant to stroke rehabilitation. For instance, in this section, we mentioned the capability of several wearable systems of monitoring sleep quality. As it is known that sleep quality affects the consolidation of learned motor patterns, it is expected that—in the near future—we will witness a growing use of wearable sensors to monitor physiological variables such as sleep quality and autonomic dysregulation.

21.6 Conclusions

The body of work discussed in this chapter suggests that the use of wearable sensors will soon become an important tool in rehabilitation, including in the context of home-based monitoring and tele-rehabilitation of stroke survivors. Different clinical applications of wearable sensors are marked by different challenges. For example, setting goals and providing feedback is quite intuitive for users in the case of LL (gait) applications where step counts, distance walked, and stair climbing measures can be used as intuitive metrics to set target levels of activity. Wearable sensors to obtain such metrics can be unobtrusive as typically only one sensor is needed to collect data to derive such metrics, and many commercially available solutions exist. However, translating this approach to UL interventions is challenging. It may require wearing more than one IMU (e.g., wearing sensors to track the movement of multiple fingers) and doing so bilaterally. Consensus on relevant parameters that should be used to set goals and provide feedback to patients has yet to be established. In addition, approaches based on wearable sensors to encourage activity may need to be combined with behavioral interventions to assure that motor gains are sustained over time. Patients need to be engaged and care about the metrics provided by wearable sensors. It is important that patients relate changes in motor behaviors and health outcomes (e.g., decreased stroke risk). In the context of rehabilitation, setting achievable targets that encourage the performance of new activities appears to be an effective strategy to maximize adherence to an exercise program and sustain changes over time. In the context of home-based monitoring and exercises, systems based on wearable sensing technology (examples in Sects. 21.2.2 and 21.2.4) enable the performance of therapeutic exercises, often in a non-immersive virtual environment with gamification, and are a great tool to provide feedback and motivation to patients.

Another factor to consider is accessibility to commercially available wearable sensors for at-home deployment. Currently, about one fifth of the adult population is using a wearable device (i.e., either a smart watch or a wearable fitness tracker) on a regular basis [181]. From a prevention perspective, this is a positive trend as many people are encouraged to develop healthy habits and pay attention to their motor activities, sleep quality, and physiological data. However, reports show that young adults and women from higher-income households and with a college education are among the top users of these technologies. Literacy level and socioeconomic status appear to be highly correlated with the adoption of wearable technology and its use to facilitate adherence to a healthy lifestyle. In addition, the algorithms used in consumer-grade devices often show limited accuracy in patients with motor impairments, which negatively affects the adherence and usefulness of these systems in a rehabilitation context. As activity trackers collect a big amount of data on physical metrics and health, another issue to be carefully considered are the barriers to data sharing that one might encounter either because of patients' preference or because of regulatory requirements. As wearable devices become part of our daily lives and clinical care, ethical considerations about data sharing and use of the data (e.g., for secondary analyses) need to be carefully considered. Also, the use of prompts to change patients' behavior has to be carefully considered from an ethical standpoint.

Nonetheless, wearable sensors are a unique tool that allows to gather data inside and outside the clinic for a longer period than the more classical data snapshots of movement and physiology taken with classical assessment methods used in rehabilitation. In the future, the use of wearable sensors during daily life activities could allow researchers to precisely evaluate the effects of novel therapies (i.e., new rehabilitation approaches or regeneration therapies). This would enable the implementation of precision rehabilitation in which clinicians design patient-specific interventions, set clinical objectives, track patient's response using wearable sensors, and periodically evaluate the effectiveness of the ongoing intervention based on the recovery trajectory defined by the time series of clinical score estimates derived from wearable sensor data.

In conclusion, wearable sensors and their applications in stroke rehabilitation are progressing at a fast pace in research laboratories. Their use in the clinic remains sparse.

Improvements in the adoption of this technology, which has been shown to be clinically useful in many ways, could be achieved by a stronger focus on involving end-users in the early stages of the development of wearable technology solutions. Besides, a stronger focus on developing systems that are very simple to use and require virtually no set-up time would benefit adoption as clinical sites are often extremely busy and every minute of clinicians' schedule is typically fully booked. To achieve a ubiquitous implementation of wearable sensors, researchers, clinicians, stroke survivors, caretakers, and engineers need to work together. It is apparent that more work and research need to be done to improve currently available wearable sensors and systems in terms of their usability and applicability in a clinical setting. However, we should emphasize that research that has relied on wearable technology to collect data from stroke survivors has allowed us to gather important information that we would have not been able to collect without the use of wearable sensors and systems and that such information is reshaping stroke rehabilitation.

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