Development of an Evaluation System for Upper Limb Function Using AR Technology

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ABSTRACT

This paper develops a prototype system for evaluating upper limb function that combines Internet of Things (IoT) and Augmented Reality (AR) technology. IoT builds the network of patients, test environment and doctor's surgery from which the system gathers and exchanges data such as the speeds and locations of hand movement. With the help of AR technology, the real-world test environment is overlaid with the information (e.g. the instructions from doctors, the progress of evaluation) gathered from the IoT. Compared to the conventional system, the detailed information of hand movement supports further assessments and the instructions generated in the AR scene for patients relieve the burden of doctors. The control experiments were conducted to explore the effects of the object size, the existence of obstacles and the hand dominance on the upper limb function using the developed system. The results verified the validity of the developed system.

CCS CONCEPTS

• **Human-centered computing → Mixed / augmented reality**; *Information visualization*; • **Hardware** → Wireless integrated network sensors;

KEYWORDS

Upper limb rehabilitation, function evaluation, IoT, AR

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1 INTRODUCTION

The primary function of the upper limb is to move the hand around the body to interact with the surroundings as a manipulator. The shoulder, elbow and wrist rotation movements are responsible for positioning the hand at the desirable place while the hand is for handling objects, such as grasping, manipulation and release [1]. Upper limb function evaluation is generally implemented during rehabilitation among the patients who have upper limb impairments or persons who use an upper limb prosthetic device. The results can provide evidence for making rehabilitation plans and further enable measuring the rehabilitation progress. The commonly used function tests used in upper limb rehabilitation, e.g., Box and Block Test (BBT) [10], Manual Function Test (MFT) [11], Simple Test for Evaluating Hand Function (STEF) [6], Southampton Hand Assessment Procedure (SHAP) [8], Wolf Motor Function Test (WMFT) [13], examine integrated functions of the arm and hand. The patients are usually instructed by a rehabilitation therapist to grasp or pinch objects in different sizes and shapes, carry them to a designated place (usually with obstacles in the movement trajectory) and finally drop/insert the objects. The score is measured through counting the number of transferred objects within a fixed time or measuring elapsed time in moving specified number of objects.

During the whole evaluation process, the rehabilitation therapists give instructions, fill the examination sheet and calculate scores, while the patients follow the instructions and complete the task [6, 8, 10, 11, 13]. The test administration for therapists is however time consuming and the repetitive motions may make the patients feel tired and boring. In addition, the scorings in most function tests are relatively simple by just measuring time or counting the number of objects. Only little evidence on the condition of upper limb function can be acquired. But the comprehensive information contained in the grasping force, hand movements trajectory, timing of muscle activation and some other factors that influence the ability to manipulate activities are necessary both for functional assessment and recovery evaluation in rehabilitation. Especially they would support to make a more detailed and accurate rehabilitation plan.

To improve the performance of the conventional function tests, some studies try to employ wearable sensors or cameras to capture the movements of upper limb. Chua et al. created a computer vision system to capture the motions of patients' arms. The system could detect the arm motions and measure the muscle strength [2]. Study of [5] developed a digital BBT system. The system automatically locates the blocks, counts the number of the moved blocks, and then scores the results that can be sent to the doctors' office remotely. It also provides additional information such as the hand movement, speeds and locations for the clinicians to perform further outcome assessments of the patients. The system is designed to be used by the patient himself without the instructions of the doctors. The system may work well in the case of BBT since the task of BBT is easy to understand and operate. But in the case of a relative complex function test, e.g., MFT, the developed system may not appropriate. The MFT has 8 main tasks and each task includes 3-6 sub-tasks. It's not realistic to ask the patients to remember the details of every task and their instructions in the functional evaluation.

Our objective is to develop an upper limb functional test system that has multiple sources of data gathered from not only the subjects, but also the test environment. Thus, the system owns better understanding of subjects' movements and enough knowledge about the test environment. At the same time, the system can provide an intuitive way to explain the data gathered and give instructions based on its knowledge of the environment, so that the system can interact with the subject. The combination of Internet of Things (IoT) and Augmented Reality (AR) gives us the power to achieve this goal. IoT builds the network of subjects, test environment and the doctor's surgery, thereby enabling these *Things* to connect and exchange data. AR technology enhanced the current perception of reality where the real-world test environments are augmented with the operation instructions and the visualized data. The system is expected to improve the rehabilitation experience of the patient and reduce the burden of doctors.

The paper is organized as follows: after giving detailed explanations of conceptual framework of the proposed system (Section 2), we present details of the developed system prototype (Section 3) and describe the experiment and its results (Section 4). We then draw some conclusions and outline the future work in Section 5.

2 CONCEPTUAL FRAMEWORK

The conceptual framework of the evaluation system for upper limb function is shown in Fig. 1. The system connects the patient, test environment and doctor's surgery through network. They all considered as *Things* in the network. Information is gathered, used and exchanged among the *Things*. With the help of AR technology, the system creates an immersive test environment where the patient can interact with it and observe the visualized the data acquired from the *Things*. IoT is the data foundation of the system while AR is a tool to present the data in an elegant easy-to-understand fashion. The combination of IoT and AR improves the experiences for both doctors and patients when compared with the conventional evaluation system for upper limb function.

2.1 Information From Things

Information from the patient and test environment basically plays two important roles: 1) To help the system attain comprehensive knowledge that are necessary for function assessment and recovery evaluation in rehabilitation; 2) To provide enough information for interactions between the patient and test environment.

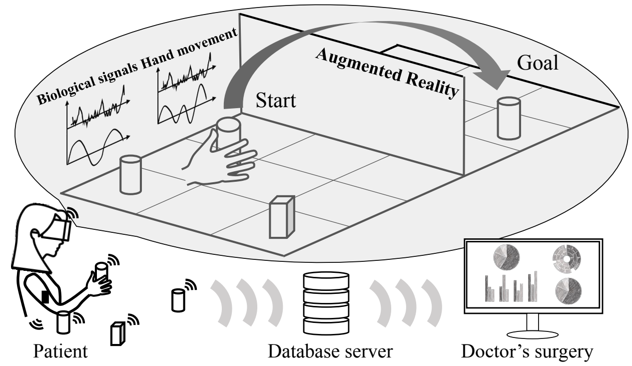


Figure 1: System conceptual diagram

In the first case, the comprehensive knowledge that helps in functional assessment and recovery evaluation generally includes grasping force, timing of muscle activation, hand movement trajectory and other factors related to the dexterity of manipulation activities. They can be acquired by measuring the bioelectrical signals and biomechanical signals of the patient's upper limb. For example, grasping force and timing of muscle activation are estimated from the electrical activity of muscle tissue and they are detected using electrodes attached to the skin (electromyography). The hand movement trajectory is determined by the position and orientation of the upper limb which are measured by the accelerometer and gyroscope, respectively.

In the other case, the interactions between patients and test environment are based on the full understanding of the system to the test environment. They include but not limited to the automatic scoring and the instructions given by the system. The scoring differs in various evaluation system. For example, the BBT is scored by counting the number of blocks carried over the partition from one compartment to the other in 60 seconds [9], the STEF calculates the scores according to the time to pick up a certain number of objects from a storage space and move them into a target space. Most of the scorings can be automatically calculated by knowing the instant location of the object. The access to the position of the objects can take advantage of the light dependent resistor (LDR) sensor which detects the intensity of light or darkness. If the objects are in their right place as instructed, the intensity of light sensed by the LDR sensors set in the corresponding place would vary, thus providing the evidence to determine the instant location of the objects. To distinguish between objects in different size and shapes, we can mark each object with Radio Frequency Identification (RFID) tags. The tags contain electronically-stored information, which allows the system to automatically identify and track objects. The instructions play an important role in the evaluation system. It tells the patient what to do next and warns on the wrong motion as what a doctor does in the evaluation process. The system gives instructions on the movement of the patient and the progress of the

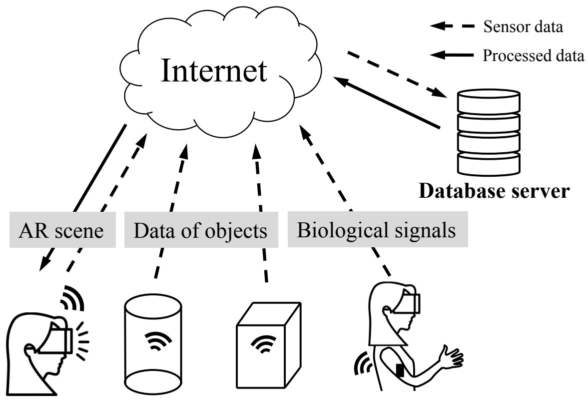


Figure 2: Information from *Things*

test. Such information could be acquired by the solutions mentioned above.

The data from the sensors embedded in the *Things* are collected and transmitted by gateway nodes and sent to a database server via networking devices (See Fig. 2). There are several different connectivity options, such as Bluetooth and Wi-Fi [7]. The network must be constructed with a proper architecture and communication technology to meet the requirements [3]. AR scene is generated in the server based on the data acquired and sent back to the display device (e.g. head-mounted display). The doctor can also retrieve the data from the database server to monitor the condition of the patient.

2.2 AR Test Environment

AR technology create an immersive virtual space where the test environment becomes interactive and digitally manipulable. Three primary roles of AR in the evaluation system are listed as follows.

(1) Visualize data from IoT. Data from the patients, the objects and the test environment is generally unreadable. It could be visualized in a understandable way and projected to the real world with AR technology. The AR scene depicted in Fig. 1 demonstrates an example of showing signals from patients and objects. Visualizing data make it easy for patients to track the scores and progress.
(2) Show instructions. The AR scene shows instructions like "Start", "Faster" or "Remove the pegs once at a time and return them to the container" [10]. These instructions guide patients to finish the test. Overlaying the instructions on the real world is a way to do the upper limb function evaluation without the supervising of doctors, thus reducing the doctors' burden.
(3) Customize the test environment. Test environment can be customized according to the requirements of the patient. If the partition between the compartments of BBT as well as the slots on the board of the STEF are simulated by computer and merged with the real world, the height of partitions or the size of the slots can be easily altered through programming to adjust the task difficulty.

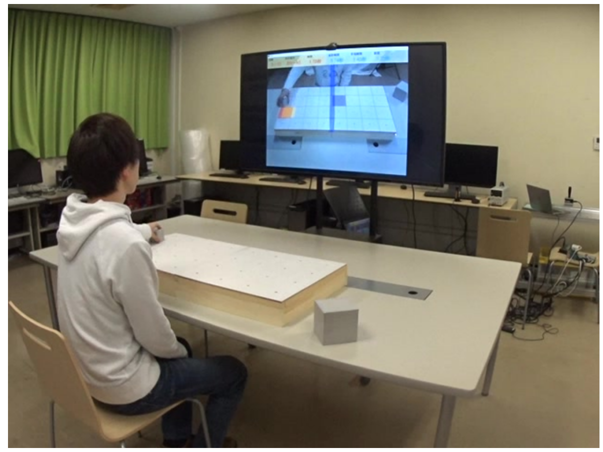


Figure 3: Test environment

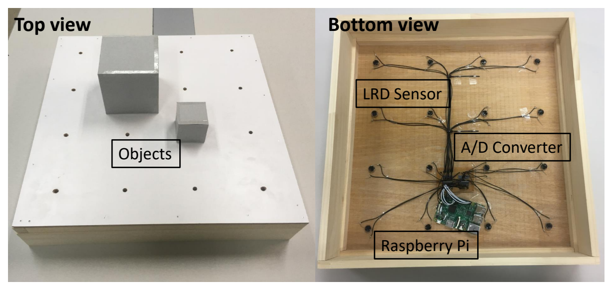


Figure 4: Test board and objects

The construction of AR test environment is a relative complex problem, which needs to align sensed or measured information exactly overlaying where they should be in space. The information from *Things* should offer enough information for constructing the AR scene.

3 PROTOTYPE SYSTEM

We develop the prototype system according to the conceptual framework. The test environment of the developed system is shown in Fig. 3. Patients are seated at a table, facing a computer monitor that displays the enhanced test environment. Two square boards are put side by side on the table. The patient is instructed to move the objects from one board to a specified location in the other board as soon as possible. It is scored by measuring the total time of performing 10 repetitive movements as instructed. Less consumed time on the test indicates better upper limb dexterity.

3.1 Data Acquisition

The data from the patient, the test boards and the objects are the foundation of the system and the network that connects these *Things* makes the data flow and exchange in the system. The developed system retrieves data from the embedded sensors of test board and objects. The test board and the objects are shown in Fig. 4.

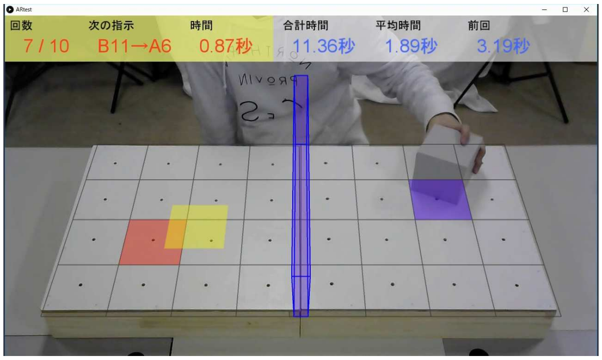


Figure 5: AR scene

The test board can sense the objects in 16 locations which corresponds to 16 small holes in the top view of the boards. The holes are drilled for inserting LDR sensors to detect the light intensity. The light intensity will decrease if the objects cover the holes, thus providing the evidence for acquiring the location information of the object. The locations of objects serve the system for offering the time consumed in each movement or feedback that if the patient moves the objects as instructed. The data of sensors are read by the client (Raspberry Pi) via a A/D converter (MCP3208-CI/P). The communication between client with A/D converter uses Serial Peripheral Interface bus (SPI) that only uses four pins on IC packages.

The objects can sense their orientations and positions by means of an add-on board for Raspberry Pi called Sense HAT. The Sense Hat integrates gyroscope, accelerometer and magnetometer together, which enables the estimation of orientation and position [4]. The Sense HAT as well as the Raspberry Pi are fixed inside the objects. The data from Sense Hat can be easily accessed with a Python library provided by the community of Raspberry Pi. It provides the hand movement trajectory, speed and locations for the doctors to perform further outcome assessments of the patients.

The system uses Raspberry Pi as clients to log data from the LDR sensors, the Sense HAT and the webcam to the database server. The clients and the database server are in the same local network and connected through Wi-Fi. In the side of the client, we use Fluentd as the data collector. Fluentd manages the data in JSON format and uploads the JSON logs to the server . We also created a dashboard using Elasticsearch in server to visualize and analyze the data from Fluentd.

3.2 AR scene

The webcam captures the test environment and feeds the streams in real time to the server via client, offering the current perception of reality. With the logged data from sensors and the current perception streams from webcam, the database server constructs the AR scene using Processing, which is a flexible software sketchbook for dealing with visual arts [12].

The monitor displays the constructed AR scene. An example of a frame is given in Fig. 5. The upper part of the figure shows the information of 6 items on the progress of function evaluation, including the current movement number, the next instruction, the elapsed time of current movement, the total elapsed time, the average time consumed in past movements and the time consumed in last movement. Each test board is segmented into 16 grids equally in the AR test environment. The grids with purple and red denotes the starting and the target, respectively. The dynamic yellow square gives the cues on moving direction of target grid. A computer simulated partition is set between the board as obstacles. The height of the partition can be set according to the requirements. It is used for increasing the test difficulty. It is worth noting that a head-mounted display could bring better experiences, but the system uses a computer monitor with a webcam for simplicity.

4 EXPERIMENT

The experiments were conducted to verify if the developed prototype system functions well. Five students volunteered for this study. All subjects were males. And their ages from 22 to 24. The subjects were instructed to move the objects from one board to a specified location in the other board as soon as possible. Ten movements are considered as one set of experiment and the instructions of the movements are given one by one after the current movement is finished. Rest is not allowed between the movements. The average time for each movement is recorded as the score of the subject. See Fig. 3 for test environment.

We explored the effects of three variables on the dexterity of upper limb to test the system. The first is the size of the object. Two cubes in different side length were prepared for the experiment. One is 5 centimeters, the other is 10 centimeters. The weight of the cubes are both about 200 grams with sensors inside. The second is the existence of obstacles in the movement trajectory. A virtual partition can be generated between the boards and used as obstacles. The subjects are asked to carry the objects from one board to the other with or without the partition. The third is the hand dominance. The subjects use their dominant hands and non-dominant hands separately to finish the task. The control experiment involves three variables and each variable has two patterns. Thus eight sets of experiments are needed to investigate their relationship. The experiential conditions are listed in Table 1. The average time of movement in different experiential conditions is shown in Table 2. The data are organized and plotted in Fig. 6.

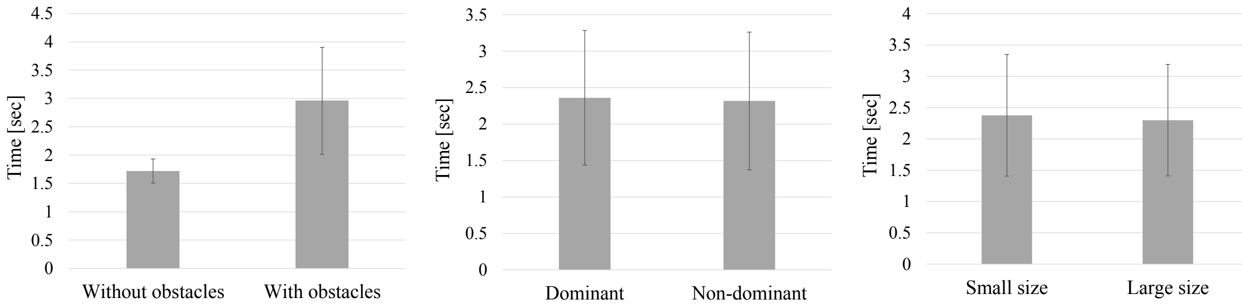
Table 1: Experimental conditions

Condition No.	Partition	Object size	Hand dominance
1	With	Small	Dominant
2	With	Small	Non-dominant
3	With	Large	Dominant
4	With	Large	Non-dominant
5	Without	Small	Dominant
6	Without	Small	Non-dominant
7	Without	Large	Dominant
8	Without	Large	Non-dominant

Figure 6a shows the effects of obstacles on the upper limb function. The average time of movement without obstacles was 1.72 seconds while the average time of movement with obstacles was

Table 2: Time of movement in different conditions [sec]

Condition No.	Subject A	Subject B	Subject C	Subject D	Subject E
1	1.544 ± 0.34	1.922 ± 0.53	1.485 ± 0.24	2.041 ± 0.40	1.787 ± 0.38
2	1.528 ± 0.26	1.800 ± 0.34	1.985 ± 0.66	1.669 ± 0.48	2.067 ± 1.95
3	1.769 ± 0.47	1.738 ± 0.30	1.816 ± 0.45	1.608 ± 0.19	1.584 ± 0.32
4	1.535 ± 0.19	1.806 ± 0.44	1.945 ± 0.70	1.485 ± 0.27	1.279 ± 0.20
5	2.685 ± 0.71	3.241 ± 0.58	3.898 ± 0.86	3.910 ± 0.91	1.233 ± 0.23
6	2.052 ± 0.28	3.722 ± 0.96	3.715 ± 0.74	3.935 ± 0.70	1.344 ± 0.36
7	2.494 ± 0.73	3.409 ± 0.51	3.183 ± 0.50	4.059 ± 0.86	1.798 ± 0.83
8	2.647 ± 0.52	3.346 ± 0.54	3.496 ± 0.32	3.618 ± 0.88	1.385 ± 0.19



(a) Effects of obstacles **(b) Effects of hand dominance** **(c) Effects of object size**

Figure 6: Effects of three experimental variables on the upper limb function

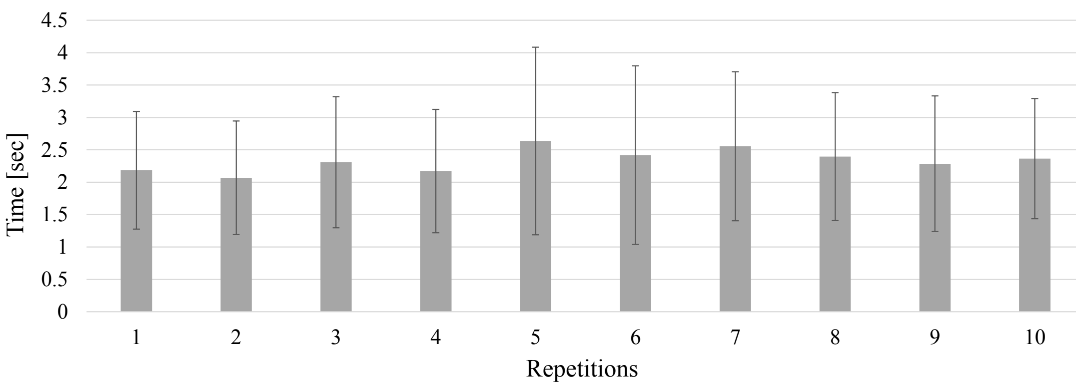


Figure 7: Time of movement in each repetition

2.96 seconds. If the computer simulated partition is set between the test board, the subjects have to consider the height of the partition when carrying the object going across it, thus the movement path becomes longer. It is easy to understand that the differences in movement time between two cases (with or without obstacles). In addition, we also found that the obstacles make it easier for subjects to move the objects to a wrong grid on the board. It can be considered that the existence of the obstacles make the movement more complex, which leads the possibilities of making mistakes. The results prove that the obstacle generated by AR is effective.

Figure 6b shows the effects of hand dominance on the upper limb function. The average time of movement using dominant hand was 2.36 seconds while the average time of movement with non-dominant hand was 2.31 seconds. Dominant hand in general has better, faster, or more precise performance than the non-dominant hand, but the result shows that only little differences between the dominant hand and non-dominant hand are observed. It is because that the effects of hand dominance on the upper limb function may not be observed if the task is too easy, especially all the subjects are healthy without any upper limb impairment. If the subjects have upper limb disorders or elderly people, the effects of hand dominance may be observed.

Figure 6c shows the effects of object size on the upper limb function. The average time of movement with small size object is 2.37 seconds while the average time of movement with large size object is 2.30 seconds. We used two cubes with the side length of 5 centimeters and 10 centimeters in the experiment separately and almost the same results were acquired. Since all the subjects are healthy and young, the effects of the object size on upper limb function may not be observed easily. It is worth noting that the locations of objects are sensed by the LDR sensors embedded in the test board. The area of the objects that covers the test board affects the sensing results. The cube in large size has more chances to cover the LDR sensor than the small size, so it may get higher score than the small size. But this is not found in the results.

For each experimental conditions in Table 1, the subjects performed 10 repetitions of movement. We calculate the average time of performing eight object-moving tasks in each repetition and plot the results in Fig. 7. This experiment was conducted to check the stability of the developed system. The movement that takes the shortest time is the second repetition which takes 2.07 seconds, while the movement that takes the longest time is the fifth repetition that takes 2.64 seconds. The difference between the two repetitions is 0.6 second. Since each repetition carries the objects to the different place as instructed, the length of movement path will be also different. It seems reasonable that the movement time differs among repetitions.

We used the developed system to test the effects of the obstacles, hand dominance and object size on the dexterity of upper limb as well as the stability of the system. We successfully gathered the information from the test boards, objects and subjects. At the same time, the information was presented using AR technology. The experiments verified that the system works well. However, the subjects chosen in the experiments had no upper limb disorders, it is hard to validate the medical effect of the system.

5 CONCLUSIONS

This study developed a prototype evaluation system for upper limb function using IoT and AR technology. The developed system could acquire abundant information from patients and test environment with the help of IoT. The real-world test environment is overlaid with the information from IoT using AR, such as the instructions from doctors, the progress of evaluation, the current scores and so on. The combination of IoT and AR makes the test environment immersive and interactive. In addition, the detailed motion information of the patients provided by the system supports a further assessments. The developed system improves the rehabilitation experience of the patient and reduces the burden of doctors. The experiments verified the validity of the developed system. In the future, the experiments will be conducted not only among the healthy people but also the patients with upper limb disorders to check the effectiveness of the system in medical perspective. In addition, the system will provide more detailed information about the upper limb movement.

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REFERENCES

[1] Andrew A Amis. 1990. Part 1. Upper limb function, shoulder and elbow. *Current Orthopaedics* 4, 1 (1990), 21–26.

[2] Shengwei Chua, Geok Hian Lim, and Dhanjoo N Ghista. 2007. A quantifiable assessment device for stroke patients. In *Proceedings of the 1st international convention on Rehabilitation engineering & assistive technology: in conjunction with 1st Tan Tock Seng Hospital Neurorehabilitation Meeting*. ACM, 123–128.

[3] Osamu Fukuda, Yuta Takahashi, Nan Bu, Hiroshi Okumura, and Kohei Arai. 2017. Development of an IoT-Based Prosthetic Control System. *Journal of Robotics and Mechatronics* 29, 6 (2017), 1049–1056.

[4] Sense Hat. 2016. Sense HAT-Raspberry Pi Documentation. *Raspberrypi. org. Np* (2016).

[5] Chih-Pin Hsiao, Chen Zhao, and E. Y. L. Do. 2013. The Digital Box and Block Test Automating traditional post-stroke rehabilitation assessment. In *2013 IEEE International Conference on Pervasive Computing and Communications Workshops (PERCOM Workshops)*. 360–363. https://doi.org/10.1109/PerComW.2013.6529516

[6] Keisuke Irie, Hirokatsu Iseki, Satomi Okamoto, Kazuhiro Okamoto, Seiji Nishimura, and Kenji Kagechika. 2017. Development of the modified simple test for evaluating hand function (modified STEF): Construct, reliability, validity, and responsiveness. *Journal of Hand Therapy* (2017).

[7] Holger Karl and Andreas Willig. 2007. *Protocols and architectures for wireless sensor networks.* John Wiley & Sons.

[8] Peter J Kyberd, Alessio Murgia, Mark Gasson, Tristan Tjerks, Cheryl Metcalf, Paul H Chappell, Kevin Warwick, Sian EM Lawson, and Tom Barnhill. 2009. Case studies to demonstrate the range of applications of the Southampton Hand Assessment Procedure. *British Journal of Occupational Therapy* 72, 5 (2009), 212–218.

[9] Virgil Mathiowetz, Gloria Volland, Nancy Kashman, and Karen Weber. 1985. Adult norms for the Box and Block Test of manual dexterity. *American Journal of Occupational Therapy* 39, 6 (1985), 386–391.

[10] Virgil Mathiowetz, Karen Weber, Nancy Kashman, and Gloria Volland. 1985. Adult norms for the nine hole peg test of finger dexterity. *The Occupational Therapy Journal of Research* 5, 1 (1985), 24–38.

[11] Ryuichi Nakamura and Sanae Moriyama. 2000. Manual function test (MFT) and functional occupational therapy for stroke patients. *Tokorozawa, Japan: National Rehabilitation Center for the Disabled* (2000).

[12] Casey Reas and Ben Fry. 2006. Processing: programming for the media arts. *AI & SOCIETY* 20, 4 (2006), 526–538.

[13] Steven L Wolf, Deborah E Lecraw, Lisa A Barton, and Brigitte B Jann. 1989. Forced use of hemiplegic upper extremities to reverse the effect of learned nonuse among chronic stroke and head-injured patients. *Experimental neurology* 104, 2 (1989), 125–132.