The Digital Box and Block Test

Automating Traditional Post-Stroke Rehabilitation Assessment

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***Abstract* — The Box and Block Test (BBT) is a post-stroke assessment that measures unilateral gross manual dexterity. Commonly used by doctors, nurses and rehabilitation therapists to evaluate rehabilitation progress, the test administration however is time consuming and labor intensive. Appointments need to be scheduled for patients to visit hospital clinics or the therapists to perform at-home visits. We present the Digital Box and Block Test (DBBT) that enables deployment in residential spaces. The system automatically recognizes the two sides of the box, blocks inside of the boxes, and then scores the results that can be sent to the doctors' office remotely. The system also provides additional information such as the hand movement, speeds and locations for the clinicians to perform further outcome assessments of the patients. In this paper, we discuss the role of the technology, how it improves the current practice, and describe the system implementation and future directions.**

Keywords - Telemedicine; Post-Stroke Screening; Depth Camera; Computer Vision;

I. INTRODUCTION

Technology is changing the scope and quality of healthcare through applications such as telemedicine and home health technology by offering a cost-effective and accessible means to manage chronic disease [1]. Patients with chronic disease are increasingly taking a proactive role in monitoring and maintaining their health, e.g., doing rehab practices to improve their daily skills. One of the most pressing health issues we face today is stroke. Statistics from Centers for Disease Control and Prevention indicates that stroke is the leading cause of serious, long-term disability in the United States [2]. While more and more stroke rehabilitation therapy are conducted in patient's home, care providers still requires patients to visit the clinic to perform the clinical assessments.

We investigate a computational tool – the Digital Box and Block Test (DBBT) – that can help medical professionals record and assess rehabilitation progress of stroke patients with easy setup. Embedding this technology in the residential spaces could also help patients to relearn and recall how to use their arms, hands and fingers. With the system, care providers would be able to more precisely detect, track, and monitor patient's post-stroke functional motor improvements remotely.

A. The Box and Block Test

The Box and Block Test (BBT) is a clinically validated manual dexterity test that instructs patients to move blocks from one compartment of the box to the other in one minute for each hand [3, 4, 5, 6]. The examiner scores the test by counting the number of blocks a patient carries over during the test. Test configurations, steps and normative data were reported by Mathiowetz, et. al. in 1985 [7]. A test box and a partition in the middle should be constructed precisely and placed on a desk as shown in figure 1 left. The patient should be seated on a regular chair and facing the box in front of the examiner so that the examiner can monitor and count the blocks being transferred. One hundred and fifty blocks should be placed in one of the compartments on the same side of the patient's dominant hand. Prior to the test, the patient is allowed a 15-second trial period. The patient should place his/her hands on the sides of the box as the preparation right before the test begins. During the tests, the patient should pick up only one block and transport it over the partition before they can place the block in the other compartment. The procedure begins with the dominant hand for one minute, and then the same procedure repeats with the non-dominant hand.

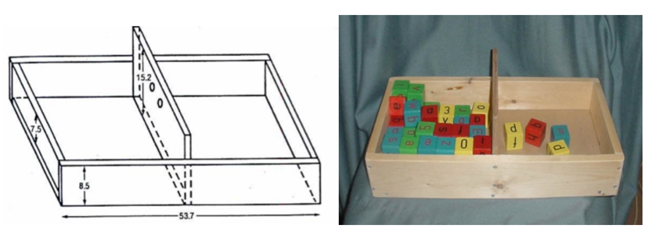

Figure 1. Construction Drawing for Box and Block Test (Left); The Sample of the Box and Block (Right) (Courtesy of Richard Wilson)

Even though the test has been validated and reviewed with test reliability, the counts of blocks transferred from one side to the other do not represent the full range of motions involved in grasping, lifting, and releasing of a block. To examine patient's hand and arm motions in performing the Box and Block Test, clinicians need to

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record videos and observe them afterward. The analysis of the video results can be subjective and with low inter-rater reliability. Furthermore, the recording, review and analytical process are labor intensive and time consuming.

B. The Digital Box and Block Test (DBBT)

Our system, the Digital Box and Block Test (DBBT), goes beyond basic recording functions to enable doctors, caregivers, and patients to analyze manual dexterity data. Our prototype system can quantify and record the data during the test. Based on the traditional BBT configurations, we implement an additional overhead depth-camera, such as Microsoft Kinect, that connects to a host computer to detect and record the motion data during a test session (Figure 2).

Figure 2. The configuration setup of DBBT

After a brief review of related works, we describe the configuration and implementation of DBBT and possible future directions.

II. Related Work

Many research projects focused on assessing and rehabilitating the motor ability of patient's upper extremity. A common approach is to use robotic devices for hand rehabilitation [8]. Some of the robotic prototypes can even help the patients to improve their manual dexterity. For instance, Broeren et al. created a robotic arms with VR system that enables the patients to play specific games through grasping the sensing device [9]. They argued that appealing VR gaming environment motivates patients to engage in rehabilitation activities, and then significantly improves their motor ability and manual dexterity. Eletha et al. collected these types of robotic prototypes and created a framework for designing stroke rehabilitation devices [10]. They argued that the simple objectives, such as moving the objects from location A to B, and appropriate cognitive challenges with meaningful tasks, such as moving objects in specific order, are the crucial factors for stroke rehabilitation devices.

Instead of deploying expensive robotic devices, other researchers employed wearable sensors or cameras to capture patient's movement data. For example, Gazihan et al. built a series of games for post-stroke patients [11]. However, the focus was on improving patient's quality of life instead of helping care providers to assess patient's stroke recovery performance. Chua et al. created a computer vision system to capture the motions of patient's arms [12]. They measured both the arm motions and the muscle strength, and found correlations between both variables. Because these systems are created from scratch for stroke rehabilitation, they have to validate whether the values of the movements, speed, forces and accelerations are meaningful clinically.

Instead of creating the test from scratch, Wade et al. developed a prototype that automates the Wolf Motor Function Test (WMFT) [13] and collected a richer dataset in addition to passing or failing the criteria that the original WMFT does [14]. In the system, the participants need to wear a set of sensors in order to detect the position of the arm as well as the accelerations for each joint. WMFT is also a clinical validated test [4] for post-stroke patients in which the practitioners ask the patients to move their arms in indicated positions to evaluate their improvements. Similar to their approach, we take the BBT as the basic infrastructure, and add the computational values on top of the original test, such as automated screening process, and capturing additional information.

III. System Configuration and Implmentation

As shown in Figure 2, except the existing box and blocks infrastructure, we only add an overhead depth camera, such as Microsoft Kinect, to detect the number of blocks and the hand movements. The depth camera needs to be on the box with about 80cm height from the box. As long as the camera can see the box with the heights, the system can calibrate itself for detecting the box, blocks and hand.

A. Software Components

DBBT is implemented by using OpenNI [15] and OpenCV [16]. OpenNI framework provides an application-programming interface (API) for creating natural interaction applications. This API includes the communication interface with low-level depth sensors, such as Kinect and Xtion, and some basic computer-vision algorithms. In order to fulfill the additional needs, we adopt OpenCV for further image processing. The detection of blocks and users' hands are vulnerable to environmental factors, such as ambient light, variegated background and even user's hands. The algorithm we developed relies on the following key steps: 1) Modeling and filtering the desktop and box; 2) Slicing the filtered depth images for block counting; and 3) Detecting the hand above the blocks.

B. Modeling the desktop and box

The first step is modeling the desktop surface and the wood box that contains blocks. After capturing 100 frames from Kinect's depth sensor and calculating the mean depth pixel by pixel, the program estimates the distance to the surface and center partition of the box at each pixel in the image, and then save it as a mask for the depth filter. As shown in Figure 3-B, with this mask, the system can filter out the desktop surface and the box for detecting hands and blocks.

As there is a distance between the infrared light emitter and the infrared light depth camera, the center partition will generate an obvious shadow where the depth values are incorrectly estimated. When user's hand move over the shadow, there will be numerous black spots on the hand's depth image, thus the hand tracking and blocks detecting will be affected. Our solution is to employ the *Findcontour* algorithm in OpenCV to determine the position and size of the box, and then calculate the position of the center partition as shown in Figure 3-C. By adding a bit larger rectangle covering the center partition, we get the final mask image without any detective shadow.

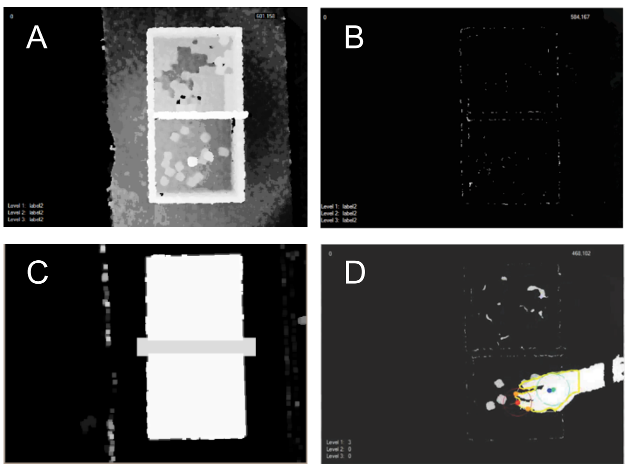

Figure 3. A: the raw depth image; B: the depth image after filtering out the environmental depth information; C: The detection of the box; D: The system is capturing a hand and few blocks transferred from one side to the other side of the box.

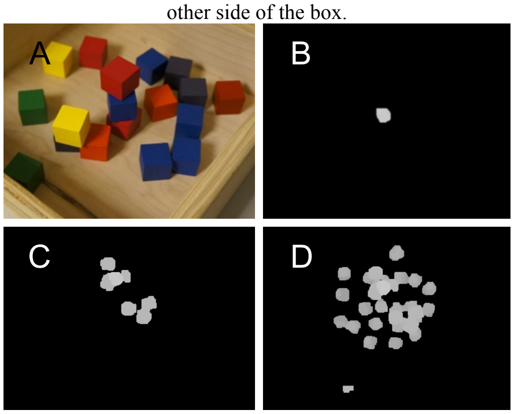

Figure 4. A: The actual blocks on one side of the box; B: The top level in the depth image; C: The center level of in the depth image; D: The bottom level in the depth image.

C. *Counting the number of blocks*

It is difficult to detect blocks in 3-Dimension space of the small wood box using color camera. When the blocks are stacked with each other, the camera cannot detect all blocks in different levels. Instead of the slower approach by using Point Cloud Library (PCL) [17] that tries to detect the feature points of each block, our algorithm tries to recognize the blocks from the contours in different depth distance. From the bottom of the box, we slice the depth images into three levels for fulfilling the possible conditions as shown in Figure 4. Each level contains 1-inch depth information since BBT uses 1-inch wooden blocks. In each level, we dilate the depth image to avoid some noise spots, and erode them to get the correct contours. Dividing the total area of the contours by area of a single block yields the number of the blocks in each level. Summing all the results in each layer yields the total number of the blocks.

D. *Detecting the Hand*

After filtering out the surface of the desk, box, and existing objects in the depth image as shown in Figure 5, the system could easily get the locations of the hand through finding the largest contour in the scene. The location of the palm center then can be computed by finding the largest circle in the contour. Through calculating the intersections between the contour and convex hull, the system could also get the fingertips that are not obscured. Using the center partition of the box as the dividing line, the computer can automatically determine whether the hand has moved from one side to the other. According to the rule of BBT, one valid movement requires not only transferring at least one block, but also moving entire palm to the other side. Besides, the location and timestamps of the moving hand are recorded, and saved to binary files for remote analysis.

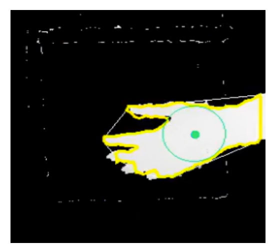

Figure 5. The system recognizes the largest contour as the hand after filtering out the box, blocks and the desktop surface. The white polyline is the convex hull. The yellow lines are the contour of the hand.

IV. Results

The prototype is built based on an Intel Core i7 computer with a Microsoft Kinect depth camera. Since we use a lightweight algorithm to detect the objects, our system runs at a sufficient rate (>25 HZ) for interactions. Figure 6 shows the number of the blocks estimated by the algorithm we described. Since the algorithm employs the area of the blocks captured by the depth camera for the block-counting estimation, it could lose some blocks due to various conditions, such as obscured blocks. After several times of tests, we found that the system starts to lose blocks after 20 blocks are transferred. However, the system has about 90% of accuracy when 80 blocks are transferred. The detail data is represented in Figure 6.

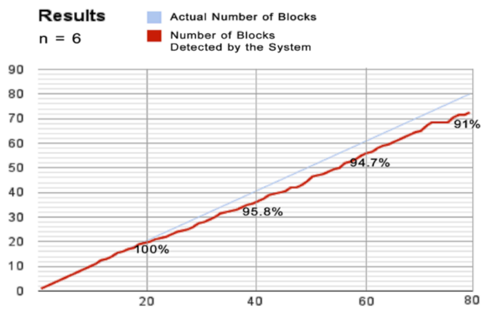

Figure 6. The red line indicates the number of blocks recognized by the system. The light-blue line indicates the actual number of blocks transferred from one side of the box to the other.

V. Future Work

Many researchers mentioned the importance of the enjoyable rehabilitation games for the post-stroke patients [9, 18, 19]. In the current stage, we build a system that can detect the patient's performances of their stroke hands based on the clinically validated screening test. In the near future, we will add a gaming system on top of the current system for the patients to relearn how to use their hands with fun and challenges. In addition, we are planning to deploy the system in residential environments for further evaluations. When we have large amount of data collected, we will be able to employ machine-learning algorithms to identify the patient's problems for different treatments in physical therapies. Designing a way to visualize these data for physicians is another crucial task in the future.

VI. Conclusion

We have described a way that automatically measures the post-stroke patients' manual dexterity by adding sensors on top of the validated test, BBT. This approach does not need additional clinical validations as long as the system is accurate enough. We also described a robust algorithm for counting blocks as well as detecting the hand's location and movements. Since the algorithm we employed is lightweight, we are able to add the interactive rehabilitation gaming system in the near future.

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