Evaluation Of The Computer-Vison Based System, Dynamic Beats, Designed To Aid In Stroke Rehabilitation

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I. Introduction

Dynamic Beats is a project focused on sensorimotor control recovery using a wearable device combined with computer-vision based software. It allows for a user to perform exercises guided by tutorial videos which are made by professionals with expertise in rehabilitation. The computer is used to analyse the position of key points on the body whilst the wearable device tracks speed and angular acceleration of a specific body part. Combined with live audio feedback, each user has their own personal experience whilst providing clinicians with accurate and useful data that they can use to assess the patients progress. This data is also used to calculate scores that reflect the quality of the patients movement and produce graphs that can be easily interpreted by the user and clinicians after initial guidance.

II. Stroke Pathophysiology

Stroke is the leading cause of death and disability worldwide [1]. Cell death because of poor blood flow to the brain causes strokes which can occur for all age groups and to cure the sequelae of Stroke, long-term effort is required. The sequalae of stroke include [2]:

- Psychological impact: depression, family difficulties
- Cognitive impact: communication, concentration, memory
- Movement problems: spasticity and hypertonicity, inversion of the foot and ankle, wrist and hand flexion

Regarding movement problems, genu recurvatum, hemiplegic shoulder pain and wrist/hand flexion are the three mean conditions that troubled patient's daily life [3]. Using hemiplegic shoulder pain as an example, up to 72% of hemiplegia occurs following a stroke [4] [5]. The syndrome is characterized by pain, swelling, hyperesthesia and vasomotor instability of the wrist and hand, coupled with shoulder pain and decreased range of motion [6]. It is well documented that physiotherapy emphasizing range of motion exercises results in positive responses from patients which occur from as little as three months from treatment starting [7].

Therefore, our goal was to help patients recover from movement problems of both upper limbs and lower limbs remotely, meanwhile providing useful data for clinical analysis. Currently, in-person physiotherapy is used but there are drawbacks such as: high cost; inefficiency, since one physiologist is limited in time and can't handle too many patients; difficulty in measuring improvement due to lack of data. Also, with the COVID-19 pandemic, remote physiotherapy is urgently needed.

With our system, patients can perform exercises focusing on range of motion at home without spending large amounts of money on physiotherapy and data is collected for clinicians. The data collected is used to produce a series of scores for each exercise which can be easily interpreted by patients and clinicians. Figure 1 and Figure 2, showing the deviation from ideal movement and the relevant angles respectively, are example graphs produced by our system.

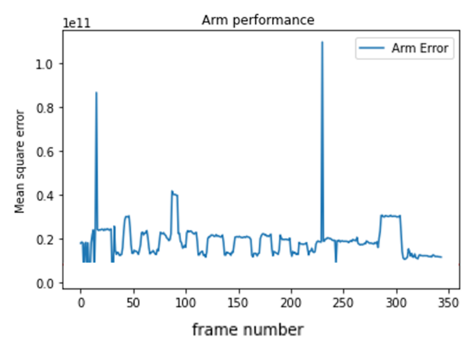

Fig. 1. Arm MSE during exercise

III. Solution concepts

Our project was constructed with a laptop and a wearable device. This rehabilitation approach was chosen as laptops are a common item in many households and it allows for augmentative and alternative communication interventions between itself the wearable device. The laptop, using freely available software, is used to evaluate fine movements accurately and perform calculations on gathered data whilst also providing real time audio feedback. The wearable device can analyse kinematic and kinetic parameters of

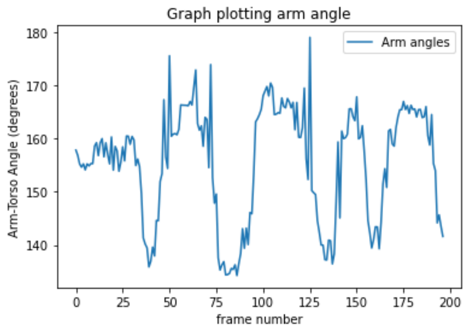

Fig. 2. Arm angle during exercise

human movements which can then be sent to the laptop via Bluetooth and hence musculoskeletal functions can be quantitatively assessed [8].Through these concepts our system can provide a low cost, convenient and portable solution to users without the limitation of specific user environments.

Hilde Feys highlighted sensory feedback's relevance as an assisting stimulus to the motor cortex [9]. We also found that the mirror neuron system is utilised during observation of others performing an exercise and imitation of the exercise [10]. Furthermore, Marco Franceschini's work concluded that consistent action observation with physical training is better than static image observation with physical training during the early phase of stroke recovery [10]. For these reasons we decided that audio feedback and tutorial videos in tandem would provide an optimal experience that maximises the chances of successful rehabilitation. It would also allow us to tailor the tutorials based on relevant activities of daily living such as holding objects, opening a door or eating with a spoon. We also considered that some patients might show tremor on hands or legs. Haemorrhagic strokes typically induce the onset of tremor and other movement disorders more than ischemic strokes [11] but using the wearable device fixed on limbs, we can gauge rotational speed and evaluate patients' tremor conditions.

IV. Prototypes and Design Choices

A. *Wearable Arduino Prototyping*

Our original design revolved around a Arduino Nano 33 BLE Sense which had the capacity to detect velocity and acceleration. Furthermore, the temperature sensor on the Arduino would be used to monitor the user's skin surface temperature. Using the velocity data gathered from the IMU of the Arduino we could control the playback of a song chosen by a user which would be played through a small buzzer. The song would then be disrupted if the user moves too quickly or too slowly and hence indicate to the user to change pace. The temperature sensor would be used in junction with an LED that changed colours depending on the temperature range the user was in after a calibration stage. Through this visual feedback, the user could gauge their effort levels.

This particular Arduino module was used for two reasons. Firstly, it already had many of the sensing systems integrated into the module which meant that no extra devices would be required. If additional modules had been needed, then more data would have to be sent via Bluetooth which could result in more technical issues for the user. Secondly, the small size of the module allows for the device to be placed on part of the body without adding considerable weight which may hinder the user's ability to perform an exercise; especially in the context of patients suffering with neuromuscular diseases that lead to muscle atrophy [12].

The literature states that increasing the number of repetitions is important for successful rehabilitation [13]. Using a song for audio feedback would provide motivation for the user to continue the exercise whilst also providing audio cues. The limitation of using a buzzer however, was that song choices available to the user were small as well as poor audio quality. We justified using the temperature sensor because the literature found that over exertion could lead to more damage occurring and the LED's visual feedback could prevent this from happening [14].

Initially, the data gathered from the Arduino was not sent to a central computer because this would require extra computation from the centralised device which would slow analysis of other factors detected by our system. However, this changed when we decided to play the sound from the laptop rather than a buzzer. This method had 3 distinct advantages; Firstly, the audio quality and volume improved; Secondly, the number of songs available increased; Thirdly, the Arduino no longer needed to play the notes which meant that it could gather data at a faster rate and provide more information for our system to use. We also decided to not use the temperature sensor as this required close proximity to the skin which would prevent casing the Arduino. Additionally, reading the temperature from the sensor broke the connection between the centralised device and the Arduino which slowed down the rate of data transfer, thus reducing the accuracy of graphs produced.

After many iterations, our final wearable device consisted of an Arduino Nano 33 BLE Sense that was coded to send velocity and angular acceleration data to a laptop. It was encased in a small electrical junction box adapted to the Arduino that protected the electrics from external damage and was also light enough to have no adverse effect on the patients ability to move. The box was then attached to a snappy band bracelet using velcro. The snappy band allowed the device to wrap around limbs of various sizes catering for patients of varying size whereas the velcro allowed the device to be easily removed and placed onto another body part mid exercise if needed. Figure 3 shows all components fully assembled.

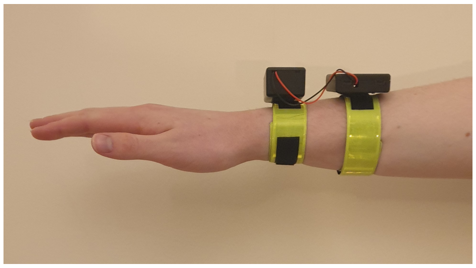

Fig. 3. Fully assembled hardware components. This includes the BLE Sense, electrical junction box, snappy bracelet and velcro.

B. Computer Vision Software Prototyping

Using the coding program Python, tutorial videos and instructions that the user could follow were displayed on the screen. Simultaneously, the user can see themselves on the screen using the in-built camera on the laptop or webcam. Having both the tutorial and themselves on screen allows the user to more accurately mimic the exercise and hence perform it with higher quality. Through the use of freely available software, Openpose, and our own developed code, we could calculate the mean square error (MSE) between the positional data of a well performed repetition and the user's repetition in real time and the angles between different parts of body such as the knee joint angle. The key points of the user's body as seen by Openpose is shown in Figure 4. The software component of our system can be divided into four parts: body key point recognition, calibration, MSE and angle calculation, final score calculation.

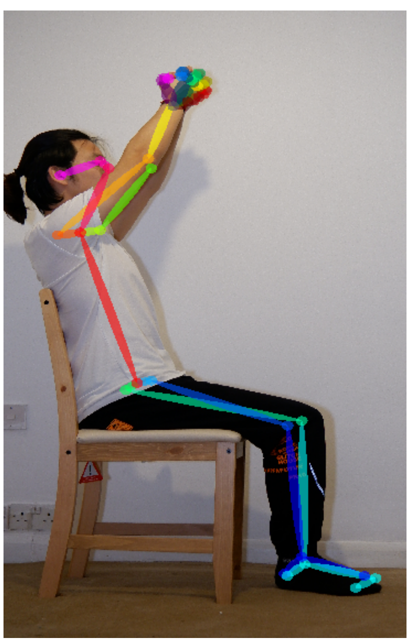

Fig. 4. Recognition of body keypoints

To recognise and track the position of key points on the users body, we used Openpose. It can recognise 25 keypoints on the body, mostly joints, and 27 key points on each hand [15] [16].

The calibration stage allows us to calculate distances between key points to then use during calculation of MSE. To do this, we applied a homography transformation which sets a connection between a pair of images taken from the same camera. Figure 5 visualises the mathematical transformation which is expressed in equation 1. During calibration the user is guided to copy 5 positions within the exercise and we take 1 picture at each position. These will be used as a reference to when the user performs the movement well and will be compared with the frames taken as the user performs the exercise in real time. Extracting 8 key points from each reference picture we are able to use 40 point pairs to calculate distances between the reference pictures and the users actual position during the exercise. The principle is that as the user performs the exercise, their posture will move closer and further away from the reference frames. We can then calculate the MSE between the live exercise frames and the reference frames using the distances calculated by the homograph transformation. This can then be plot onto a graph indicating the users deviation from the ideal movement. We chose 5 reference frames in total as our own trials show that it was the optimal compromise between the accuracy that comes with more frames and the smoothness of the program with less frames.

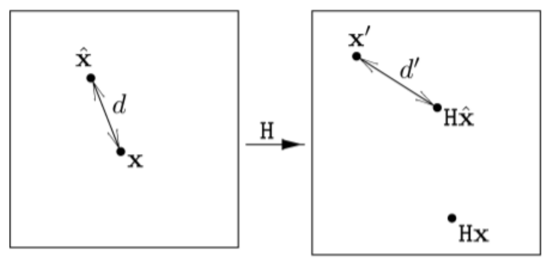

Fig. 5. Two images linked by homography H. Points x and x' are measured points, $\hat{x}$ is the point minimizing d^2 and d'^2 where d and d' are the distances x to $\hat{x}$ and x' to $H\hat{x}$ [17]

$$x' = Hx = \begin{bmatrix} x' \\ y' \\ z' \end{bmatrix} = \begin{bmatrix} h_{11} & h_{12} & h_{13} \\ h_{21} & h_{22} & h_{23} \\ h_{31} & h_{32} & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} \tag{1}$$

$(x, y, 1) : coordinates\ in\ original\ image$
$(x', y', z') : coordinates\ in\ calibrated\ images$
$h_{11} - h_{32} : parametersinhomographymatrix$

We calculated the MSE using the MSE function shown in equation 2. Every live frame had 5 MSE's calculated, one against each reference frame taken in the calibration stage. Among the 5 MSEs, we record the smallest MSE calculated. When the recorded MSE spikes higher than usual, we can see this in the plot and know that the posture at that time is far from any reference frames and is likely to be an incorrect position, indicating a poor movement. A spike that illustrates this can be seen in Figure 1. When the MSE spikes, the program also captures this frame and saves it to the laptop which can be sent to a professional via email. We decided to do this because on its own, the MSE does not tell the user or the clinician much. However, a picture allows the clinician to identify what is wrong and can give advice to the patient on how to improve their movement.

$$MSE = \frac{1}{n}\left(\sum_{i=1}^{n}(x_i - x_i')^2 + \sum_{i=1}^{n}(y_i - y_i')^2\right) \qquad (2)$$

(x, y) : *coordinates in original image*
(x', y') : *coordinates in calibrated images*

Using the key points extracted and applying simple trigonometric functions the angle between different limbs can be obtained. We believe that angles are the best way to convey the range of motion to the user as using a parameter such as distance could vary largely between patients of different sizes. For our particular exercise, we chose to compute the angle between arm and upper body and knee angle as the exercise is about emphasizing the range of arm and leg movement.

A score summarising the users performance was then calculated using all the MSE data gathered. The reason for computing a final score is to present users with a straightforward assessment of their performance during the exercise. This way the user can track their own progress in a simple manner and stay motivated when they see gradual increases in their score. These scores can also be used in a "competitive" manner between patients as the disparity in the stage of the disease they suffer from would actually be accounted for due to the nature of our calibration stage which sets the "standard" for every patient individually.

An Arduino Nano IoT is used to communicate between the wearable device and the laptop. As the laptop plays the music, the data received from the wearable is used to disrupt the music if the velocity recorded is outside of a certain range. This allows for immediate audio feedback to the patient but also provides a stimulus for the user to perform the exercise in a controlled manner. The velocity data is also summarised into a score that the patient can see. An example of how the scores are output are shown in Figure 6.

V. Relevance of the Dynamic Beats System

A. Clinical relevance

Our system provides the user and the clinician with access to velocity, acceleration and angle data coupled with calculated scores based on MSE's. It outputs this data in simple numerical scores that the user can use to track their progress whereas the

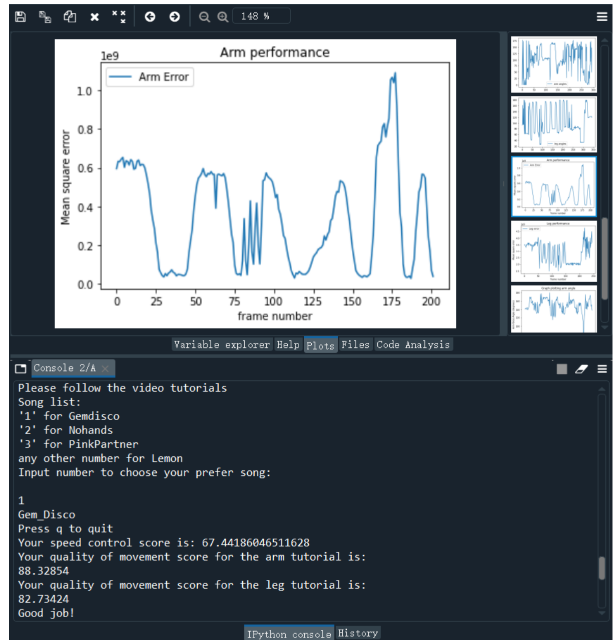

Fig. 6. Illustration of how output scores are displayed to the user

graphs recording the MSE are more suitable for clinicians to analyse in tandem with photos showing where the exercise was performed poorly. From this, the clinician can give specific instructions to each individual patient. Immediate audio feedback also aids the user in controlling their pace whilst motivating them to do more repetitions which, based on the aforementioned literature, is key to successful rehabilitation.

VI. Design Evaluation, Lessons Learned and Proposed Improvements

The functionality of the Dynamic Beats System was practically tested by different users of varying heights and gender and in different environments. We found the system was very robust both physically and regarding software. The wearable device showed no signs of breaking throughout testing and the software handled various erroneous input from users. After slight explanation the outputs were widely understood and the user experience was considered enjoyable. Over all the system provided relevant data to clinicians whilst also providing a motivational platform for patients to go through rehabilitation programs.

One of the most impressive aspects of our system was its adaptability. It can be used for a large multitude of 2D, planar exercises that do not have to necessarily be associated with stroke with just a few changes to the code. In demonstrations we exemplified that this could be used for both lower and upper limb movements but it is not limited to this as other movements such as those of the hand can also be tracked and analysed using the same software.This means that the system can act as a all-in-one integrated system for a number of neuro-muscular diseases unlike many others current systems.

However, its adaptability is derived from its heavy reliance on complicated software and computer vision. Consequently, the system suffered from a user interface that wasn't very easily navigated and could confuse some users not experienced with computers. This is especially important if the system is to be used at home with no professional nearby to help. Moreover, it was advised that the term MSE was not the best way to describe what we were showing. To improve the system in these areas we could have developed an application that provided a UI that was more user friendly and changed the MSE term to be a "deviation from ideal movement".

Another limitation that could be improved in future iterations would be to allow for 3D motions. Currently our system can only track 2D exercises due to the Openpose software used. At the cost of more complicated software, the range of exercises that can be used with the system is almost limitless.

Finally, the social and game-like aspect of our system could have been improved. Currently we provide scores that can be used in a competitive manner by patients but it is not integrated into a game. A possible solution would be to design a "Just Dance" like game where the patient must mimic the tutorial video to the beat of their chosen music. This would have increased the motivation to complete sessions.

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