Evaluating Functional Ability of Upper Limbs after Stroke Using Video Game Data

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Abstract. The aim of this paper is to develop a validated system for remote monitoring by health professionals of home-based upper limb rehabilitation by utilising action-video games, data analysis algorithms and cloud server technology. Professionally-written action-video games designed specifically for upper limb rehabilitation were used and game controllers provided continuous 3D kinematic data of hand and arm position. Assessments were made in the patient's home when they played a bespoke 'assessment' mini game controlled by 40 representative actions. An occupational therapist also undertook a blinded clinical CAHAI assessment. For each move 8 scalar variables were defined from both limbs, giving 320 covariates. There were entered into a multiple linear regression random effects model which identified 15 covariates derived from 12 movements that explained 80% of the variance in the CAHAI scores. We conclude that remote monitoring by health professionals of home-based upper limb rehabilitation is possible using data collected remotely from video game play.

Keywords: e-health, Functional ability of upper limbs, Position and Orientation data, Remote monitoring, Stroke, Video Games.

1 Introduction

Stroke has emerged as a major global health problem – in terms of both death and major disability – that will only continue to increase over the next 20 years as the population ages [4], [15]. 16 million people worldwide suffer a first-time stroke each year, more than 12 million survive. The world population is ageing significantly: in less than 60 years there will be a three-fold increase in people over 60 (to 2 billion) and a five-fold increase in people over 80 (to nearly 400 million). This will add to the number of strokes annually and lead to an increase of people

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living with the consequences of stroke in the coming years. Because of this trend, the prevalence of stroke survivors, currently 50-60 million, is estimated to reach 77 million by the year 2030.

Hemiparesis, a detrimental consequence that many stroke survivors face, is the partial or complete paralysis of one side of the body that occurs due to the brain injury. It is remarkably prevalent: acute cases of hemiparesis are present in 80% of stroke survivors [16]. Six months after a stroke, 50-70% of stroke survivors have persisting hemiparesis [6], [9].

Studies have consistently demonstrated significant, therapy induced improvements in upper limb function can be achieved, even in patients who suffered the stroke several years earlier, but only after intense, repetitive and challenging practice [11]. Limited resources, specifically lack of therapist time, are the main barriers to implementation of evidenced-based guidelines for stroke rehabilitation [16]. Conventional rehabilitation programs carried out at home, unsupervised by therapists, are fraught with low compliance [22].Video games increase compliance since the focus is on game play and fun and not on impairment [19] and perceptual-motor learning from playing action-video games transfers to real-world tasks. Since the early 1980s there have been reports in the literature of commercially available video games being used for therapeutic purposes in different patient populations. In the last five years this has escalated rapidly. There is increasingly strong evidence of value of video games in therapy. A recent systematic review [17] identified 1452 published articles up until February 2010, positive results were reported most frequently by studies using video games for physical therapy, psychological therapy, or physical activity. The results of a Cochrane review [12], indicated that virtual reality was of benefit for rehabilitation of chronic stroke patients. The review included the results from 19 randomized controlled trials (565 subjects), of which 8 examined upper-limb training, and reported a significant treatment effect for arm function (SMD=0.53, 95% CI 0.25 to 0.81).

The overall aim of our research is to develop a validated system for remote monitoring by health professionals of home-based upper limb rehabilitation by utilising action-video games, data analysis algorithms and cloud server technology. The specific aim of the study reported here is to derive and validate an algorithm which models assessment of a clinically validated measure of upper limb function namely the the Chedoke Arm and Hand Activity Inventory (CAHAI)[1] from remote analysis of the movements made by patients whilst playing action video games in their own home. We used bespoke, professionally-written action-video games (Circus Challenge, Limbs Alive Ltd; `http://www.limbsalive.com/`) designed specifically for upper limb rehabilitation.

2 Methods

Ethical approval was obtained from the National Research Ethics Committee and all work undertaken was in accordance with the Declaration of Helsinki. Written, informed consent from all the subjects was obtained.

2.1 Subjects

The subjects comprised 18 patients (age range 48-77; mean 60.8, 8 females) without significant cognitive or visual impairment; 15 were in the chronic phase after stroke defined as more than 6 months after their first ever stroke and 3 were in the acute phase defined as starting video game based rehabilitation with 2 weeks of their first ever stroke. Patients had a wide range of upper limb function as reflected in their Chedoke Arm and Hand Activity Inventory (CAHAI) scores (range 13-70, mean 46). None had previously played video games but all participated in a home-based rehabilitation programme using the Circus Challenge video games over a 3 month period. The games can be played either standing or sitting down.

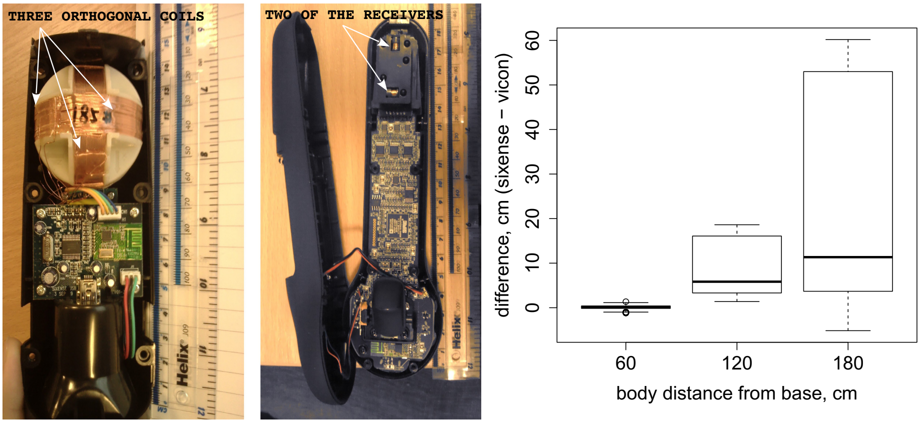
2.2 Protocol

Circus Challenge comprises 10 P.C. based video games. Control of the video games is achieved via 100 separate upper limb actions based on identified patterns of co-ordinated bimanual movements, which together form the functional bases for activities of daily living [10]. The patients were asked to play the video games of Circus Challenge in their home each day for approximately half an hour.

To derive the algorithm we built an additional 'assessment' mini game controlled by 40 representative actions, ranging from the simplest mirrored movements where the same movement is performed simultaneously by each upper limb, to co-ordinated movements where each arm and hand performed different movements in a coordinated manner. The actions in the assessment game are presented in order of increasing difficulty and the data generated from measuring the arm and hand movements whilst patients performed these actions were used for modelling purposes to derive the algorithm. Research assessments were made in the patient's own home, during which patients were asked to play the assessment mini game and an occupational therapist undertook a blinded clinical assessment of upper limb function (the Chedoke Arm and Hand Activity Inventory [1]). These assessments were made at baseline and then weekly for 4 weeks, followed by an assessment every 2 weeks for a further 6 weeks, giving 8 assessments in all.

2.3 Measurement of Arm and Hand Movements during Game Play

Commercially available game controllers use combinations of LEDs, gyros, accelerometers, and cameras to detect motion. These systems are susceptible to interruption due to line-of-site obstructions and/or must be re-calibrated throughout. We chose therefore to use game controllers by Sixense Entertainment (`http://www.sixense.com/`) to provide continuous position and orientation information by using magnetic motion tracking. This is established and well researched technology [7] and it is commonly used to measure 3D position in space. The Sixense game control system comprises one base unit powered by an USB connection and three wireless controllers. The base unit contains three orthogonally orientated emitter coils which generate an electromagnetic field and provide the reference for the position and orientation measurements of the sensors. Each Sixense controller contains three small orthogonally orientated coils as the sensors, whose positions and orientation are measured relative to the source (see Figure 1a below). The controllers in the game return three-dimensional position data and nine-dimensional orientation data with a sampling frequency of 60 Hz.



(a) Base unit (left) and controller (right) (b) Estimated measurement error

Fig. 1. Sixense controller and measurement error

2.4 Validation of Sixense Measurement System

It is well recognised that 3D tracking using magnetic fields is limited by the decay of the strength and distortion of the magnetic field with distance between the emitting source and the sensors [25]. With standard transmitters, tracking devices such as the Fastrak® (3Space Devices, Box 560, Colchester, VT 05446, USA, `www.polhemus.com`) or Flock of Birds® (Ascension Technology Corporation, Box 527, Burlington, VT 05402, USA, `www.ascension-tech.com`) can operate within 70 cm of the transmitter with errors smaller than 2%; at greater distances, increased variance is experienced [13], [14]. The purpose of this initial study was to determine the operating range of the Sixense system. In order to ascertain this, comparisons were made between the 3D position of the Sixense controllers measured using their magnetic tracking software and that measured by an 8 camera, Vicon optical motion system and Vicon iQ software.

Visual markers for the Vicon system were placed on the wireless controllers and on the base unit. There is an intrinsic difficulty in knowing the exact location of the centre of the emitter that is used as the reference point by the Sixense system and also of position of the measuring sensors in the Sixense wireless controllers, relative to these markers. That uncertainty will be reflected in the errors calculated between Sixense and Vicon.

The controllers were held by the subjects who faced the Sixense base emitter unit and stood at 60, 120 or 180 cm distance from the unit. The subjects then carried out movements so that the limbs were positioned along the three axes of the Cartesian coordinate system. The degree of agreement between the two systems was determined by calculating the limits of agreement of the two measures [2]. Figure 1b graphs the mean and 95% limits of agreement between the systems. At 60 cm (approximately one arm's length from the base unit) the mean and 95% limits of agreement were 0.09 ± 0.47 cm, giving a maximum error of measurement of 1.5%. These findings have been incorporated in the setup used at patients' homes, who are instructed to have the base unit at shoulder height and to play the game when standing at one arm's length away from the base unit. Using this set up the controllers held in the patients hands will always be only one arm's length (approximately 60 cm) from the base emitter unit, even at full arm reach. To ensure this is maintained throughout game play if a patient moves to stand more than 80 cm from the base unit while playing the game, an automatic instruction is displayed on the screen reminding them to stand closer to the base unit.

3 Data Analysis

Figure 2.a shows schematically the placement of the emitter and the three receivers as well as the direction of the x,y,z Cartesian coordinates. Briefly, subjects face both the PC screen and the emitter while holding the wireless controllers in their hands. There is a third controller strapped to patients' waist. Before any data analysis can be carried out data needs to be standardized. This is achieved by determining the spatial co-ordinates of the subject's shoulder positions and then expressing all units with respect to the subject's arm length.

3.1 Position Data and Standardization

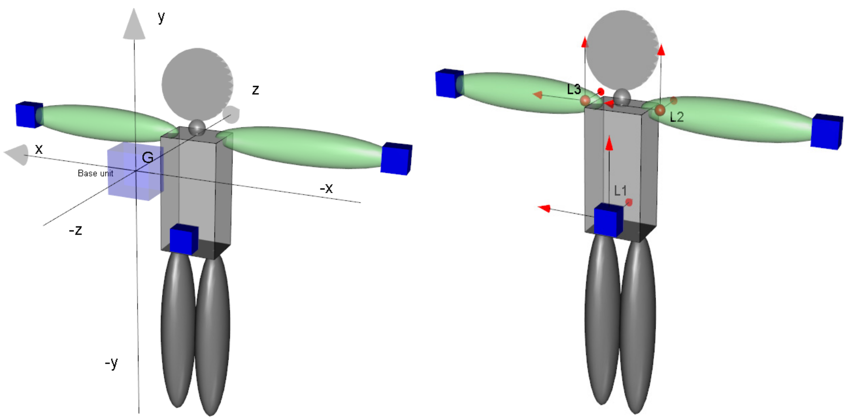
There are 3 coordinate systems (p.9 in [26]) that need to be considered to understand this process (locations are as indicated in Figure 2)

- The *Global Coordinate System* (GCS), which is in the base unit (location G). Initial measurements from the controllers are referred to it.
- The *Moving Coordinate System* (MCS), which is attached to the body and has the same orientation as the GCS. Its position (location L_1) is given by the body location where a sensor is located. The MCS moves with the body but maintains the orientation of the GCS.
- The *Somatic Coordinate System* (SCS), which is also attached to the body and positioned in the middle controller or the shoulders. Its orientation changes in space as the body rotates (locations L_2 and L_3).

We standardize the data in four steps by a set of centering and rotating stages, which are no more than changes of coordinate systems. Namely:

1. First translation, changing for the GCS to the MCS (L_1). In other terms, all 3D position data are now referred to the position of the controller attached to the body.
2. Rotation, by which the MCS is aligned with a SCS. That is, if the subject is no longer facing the base unit but is doing so at an angle θ, this rotation step ensures that the data is rotated around the *y-axis* by an angle θ.
3. Second translation, whereby we transform the data from the SCS located in the body receiver(L_1) to the two SCS located on the subject's shoulders (L_2 and L_3). Shoulder positions will have been calculated from the available data prior to this step.
4. Having all the data referred to the two somatic coordinate systems located on the shoulders, and which move and rotate in synchrony with the body, the final step involves normalizing all the measurements to remove the effect of varying arm lengths between patients.

Once data standardization is complete, all measurements will take values in the $[-1, 1]$ interval.



(a) Normal standing (b) Standing after standardizing

Fig. 2. The standing before and after standardization. The default coordinate system is right-handed (OpenGL$^{\text{TM}}$). Blue squares represent the location of the body receivers. The somatic coordinate systems in panel (b) are attached to the body, moving and rotating at the same time that the body does.

3.2 Orientation Data and Parametrizations

There are many possible manners to parametrize rotations, each with its advantages and disadvantages. They all arise, however, from *Euler's rotation theorem* which states that every orientation (this being defined as the attitude of a rigid body in space) can be expressed as a rotation by some angle θ around a fixed axis z. Thus, the axis provides the direction in which the rotation should occur and the angle indicates the magnitude of the rotation[3]. It follows from here that rotations have three degrees of freedom: two to define the axis of rotation and one to define the magnitude of the rotation. Any orientation parametrization using more than three parameters will be doing so by adding extra dimensions to the problem.

Out of the many possible parametrizations, the wireless controllers in this project provide orientation information either as a rotation matrix (9-dimensions) or as quaternions (4-dimensions). From a graphics and efficiency perspective rotations are most easily handled using quaternions[21] and this is the approach we follow. To summarize movement rotations we resort to two different metrics, namely:

- Projection angle, which is the angle formed by projecting a given coordinate-axis in the SCS in the plane formed by any two coordinate-axis in the GCS (p.41 in [26]). This allows us to detect the amount of rotation a subject is able to achieve in a given movement.
- Rotation angle, which is a metric measuring the angular distance between two given orientations (p.25 in [3]). This statistic is very useful to detect deviations from a desired controller grasp.

The more fundamental matter when it comes to handling movement orientation is in relation to the limited number of sensors available. As shown in the set-up of Figure 2, the problem is ill-defined in terms of not being able to differentiate between upper-limb rotations. That is, with only three sensors there is not enough information to ascertain whether rotations occur around the wrists, the elbows or shoulders. This ambiguity, however, is offset by the game instructions in the form of images that are being continually relayed to the patient. That means we do not need to determine which movement is being attempted but only how well a predefined movement is performed.

3.3 Kinematic Variables

There are four features that provide reliable and valid information about movement characteristics over a range of different upper limb actions; namely speed, fluency or smoothness, synchrony and accuracy. Some of those features have obvious proxy summary variables (i.e. speed and synchrony); however, what the variables should be to encapsulate smoothness and synchrony is not as clear-cut.

The kinematic variables (statistics) we have chosen to model these four features are as follows:

1. Speed - let $\boldsymbol{p}_t = (x_t, y_t, z_t),\ t = 0, \ldots, t, \ldots, T$ be the vector of normalized 3D positions at time t; then T is the total time taken to perform the movement and $\boldsymbol{p}_0 = (x_0, y_0, z_0)$ the starting position vector. The displacement distance at time t is given by

$$d_t = \sqrt{(x_t - x_0)^2 + (y_t - y_0)^2 + (z_t - z_0)^2}.$$

   The vector formed with all these displacement distances follows as $\boldsymbol{d} = (d_0, \ldots, d_T)$. Then, the total (cumulative) distance travelled by the upper limb can be calculated as $D = \sum_t \|\boldsymbol{p}_t - \boldsymbol{p}_{t-1}\|$. The most obvious statistic to measure speed is using an average speed defined as $\bar{v} = \frac{D}{T}$.

2. Smoothness - as a surrogate for this feature we use the Number of Movement Units (NMU); this is defined as the total number of peaks in the tangential speed profile between the onset and the offset of the movement [23]. A perfect smooth movement is characterized by a bell-shape velocity profile with only one peak. Therefore, it is suggested that the more ripples in the velocity profile, the more irregular the move is. In practice, since the time taken to complete each movement differs, this may be normalized dividing by T.
3. Synchrony - due to the differing characteristics of the movements being analyzed, we have two summary statistics to account for synchrony:
   - The maximum (or minimum if the movement has a phase lag) cross-correlation (p.390 in [24]) between lags $[-5, 5]$. Due to the high sampling frequency, this statistic is more prone to finding the maximum (mininum) in the time series being analyzed than a correlation measure. This statistic is suitable for both *mirrored* and *in-phase* movements.
   - The standard deviation ratio defined as

     $$(SD)_{\text{ratio}} = SD(\boldsymbol{d}^P)/SD(\boldsymbol{d}^{NP})$$

     where $\boldsymbol{d}^P$ and $\boldsymbol{d}^{NP}$ are the time series of displacement distances for the paretic and non-paretic limbs. This statistics is more suitable for *sequential* and *coordinated* movements, where one of the limbs is required to stay still.
4. Accuracy - the Range of Movement (ROM) is used as a proxy. This is defined as

   $$\text{ROM} = \text{range}(\boldsymbol{d}) = \max(\boldsymbol{d}) - \min(\boldsymbol{d})$$

   where *max* and *min* are the maximum and minimum respectively. There are alternative, more suitable ways to handle accuracy using functional data analysis by looking at deviations from an expected trajectory. This is beyond the scope of this article; for further details see [18] and [20].

There is a final distinction that needs to be made regarding these summary statistics. Some of our 40 standard movements are pure translations for which the kinematic variables are calculated as described. There is a second group of movements, however, which are dominated by rotational changes; in those specific cases, a time series of projection angles $\boldsymbol{\theta} = (\theta_0, \ldots, \theta_T)$ is used instead of $\boldsymbol{d}$ for synchrony and accuracy calculations.

3.4 Variable Selection and Modelling

One of our objectives is to provide a robust model to predict the CAHAI scores using the motion data relayed by the game. Although motion data is functional in nature (high-dimensional), the kinematic variables defined previously act as a surrogate and enter the model as scalar predictors. There are 40 movements in total which we refer to generically as LAxx (xx represents the number designated to the move in the Circus Challenge mini games; generally, the higher this number the harder is to perform the task). For each LAxx we have defined 8 scalar variables (accounting for both limbs). Hence, there are potentially $p = 320$ covariates that can be used in the model.

We propose to fit a multiple linear regression model (MLR) to the data. After discarding 7 observations with missing data, the number of observations N available for modelling was 82 (from 18 patients). Clearly, as $p \gg N$, before any attempts to fit the model are made, some variable selection strategy must be adopted. Our approach has two main steps:

- exploratory data analysis whereby we visually check scatter plots of the CAHAI scores against each covariate. Those variables/movements where there is no discernible trend are removed; and
- the correlation is calculated between all those variables remaining after *step 1*. Out of those variables highly correlated with one another only one is selected (i.e. the remaining variables are redundant).

Upon completion of the previous search strategy, 94 covariates are pre-selected. In the final step, we applied a forward selection approach using *best subsets regression* with the adjusted R^2 as the optimization criterion; for further details, see e.g. chapter 8 in [5]. The final model contains 15 variables spread across 12 movements; these covariates explain about 79.3% of the variance observed in the CAHAI scores, $R^2 = 0.793$.

The final results show that both position and orientation movements are important in the prediction of the CAHAI scores. As a final check of model adequacy, a plot of the residuals versus the fitted values is provided in the left panel of Figure 3. Although residuals clutter randomly around zero with no significant deviations from a normal behaviour, there is a slight heterogeneity amongst subjects. To account for that, we have also considered a mixed-effects model, assuming random effects for the intercept and one of the covariates. The residuals for this model are graphed in the right panel of Figure 3, showing a clear improvement in comparison with the fixed-effects model. Further evidence for this is the fact that $RSS = 820.5$ and $AIC = 547.3$ for the random-effects model while $RSS = 3459.3$ and $AIC = 573.6$ for the fixed-effects model.

3.5 Model Validation

Model accuracy can be justified by the plot of fitted value against clinically assessed CAHAI in Figure 4. The mixed-effects model provided a particular accurate result. We further used *K-fold cross-validation* (chapter 7 in [8]). Briefly, we allocate subjects into 4 random groups, each having a roughly-equal number of observations. Then we proceed by fitting a model using all groups but one; once the model is found, it is then used to predict the CAHAI scores on the unseen group. The process is repeated until all groups have been used as validation data.

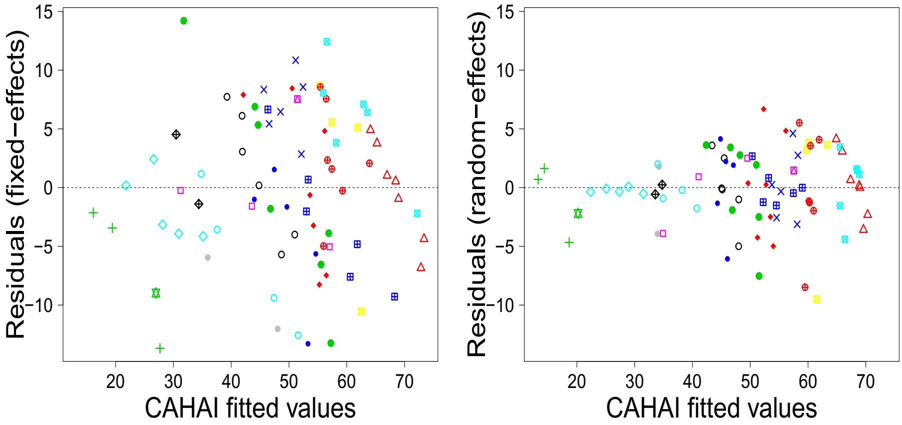


Fig. 3. Residual plots using fixed-effects model (left) and mixed-effects model (right). Different symbols and colours are used for different subjects.

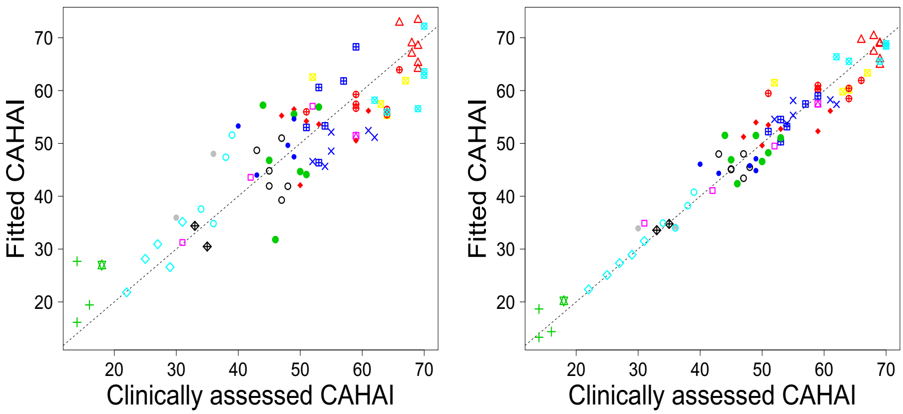


Fig. 4. Fitted CAHAI using fixed-effects model (left) and mixed-effects model (right) vs clinically assessed CAHAI. Different symbols and colours are used for different subjects.

The resulting root mean squared error (RMSE) is 10.9: a good result given the patients' heterogeneity. Generally speaking, both MLR models (fixed-effects and random-effects) fit the data well.

4 Conclusions

We have used action-video gaming data to evaluate functional ability of upper limbs after stroke. Our final model used fifteen variables only and achieved a high R^2 value predicting clinically assessed CAHAI scores. We therefore conclude that remote monitoring by health professionals of home-based upper limb rehabilitation is possible using data collected from the game controllers during game play. We are continuing validation studies to increase subject numbers and to establish the sensitivity to change of the algorithm. This will facilitate the development of expert therapy programmes delivered in the home rather than using the traditional health-centre based rehabilitation programmes with one to one therapist supervision. We are also considering nonlinear regression analysis using functional regression model [20].

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