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Assessing Rehabilitative Reach and Grasp Movements with Singular Spectrum Analysis

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ABSTRACT

An objective and accurate clinical assessment of a patient's movement disabilities are needed to provide the type and intensity of therapy for them. Current assessments in use require therapists to subjectively grade various actions performed by patients, but this is an onerous and error prone process. A common solution is to use the sensors built into consumer devices to obtain patient metrics. However we motivate for our approach of embedding sensors into objects used in established assessments which provide patient metrics in a ratified way. A significant contribution to this approach is using force sensors to capture subtle but important movements which are not easily obtained otherwise and to provide movement cues. Standard frequency domain analyses can lead to misdiagnosis which motivates for data driven approaches. like Singular Spectrum Analysis. This is used in a novel way to identify the most informative eigentriple to assess intraclass movements which are measures of the quality of a patient's upper limb movements. This is done on a set of healthy subjects who also simulated movement disorders and on some actual patients undergoing rehabilitation.

Index terms - *Singular Spectrum Analysis, accelerometer, rehabilitation, instrumented objects, stroke*

1 INTRODUCTION

Being able to perform activities considered normal is important to someone who has suffered some loss of the use of their limbs. The most common non-trauma source of this are patients who suffer stroke. The inability to live an independent life requires constant medical attention, resources and often a caregiver as well. Where it is possible to rehabilitate the use of the limbs, a customised regimen of exercises needs to be tailored to the needs of the person, depending on the extent of the disability. At the same time, progress needs to be monitored in order to assess the effectiveness of the treatment. Presently these are labour intensive tasks requiring trained therapists who record data, interpret them and keep track of what are often repetitive exercises. Compounding this is the lack of clinical skills in the home which allows only a limited transfer of the burden of care and may hamper the rehabilitation process [1]. One way to encapsulate the experience of healthcare practitioners is in the form of tests for limb function for tasks deemed essential in the Activities of Daily Living (ADL). There are a large number of such established tests which involve the movements of a patient and their interactions with various objects one of which is the focus of our work.

The use of sensors in consumer devices such as mobile phones and gaming consoles allow for a better user experience as the processors in these devices deduce the intention of the user by their movements. Embedding sensors and processors into objects - often used daily - is referred to as an instrumented object approach.

Often the signals produced by the objects are processed in the frequency domain in order to detect the underlying processes of a movement. This is also true of most current methods of analysing biomedical signals use standard time or frequency measurements. Biological signals are never so well behaved, leading to the search for newer types of analyses which we feature in this paper.

In Section 2 we review some prior work in automated assessment of patients and outline the motivation for our approach. Section 3 describes our experimental setup. The theory we use for our signal analyses is covered in Section 4. Then we report the results of our experiments in Section 5 before we conclude in Section 6.

2 ASSESSING LIMB FUNCTION FOR STROKE PATIENTS

In this section we present the motivation for our work, presenting the case for instrumenting objects used in standardised tests and review of related literature.

In formulating a test of limb functionality, enforcing a protocol for their administration provides an objective and quantitative measure of the efficacy of the patient's limb function. These measures become data that can be used to document the progress of any therapy administered and to adjust its quantum. Also, tests can be tailored to more exactly determine the nature of a disability, providing for a better regimen of therapy. Now, these tests should not require great expertise or time and effort to administer. Currently several of these tests use visual based scoring which introduces a degree of subjectivity and an inability to perceive subtle and possibly multiple motions. A solution to this is to automate and monitor the tests and/or the exercises through electronic means.

A popular approach is to use low cost consumer devices and adapt them for medical use. Of particular interest are those designed for the gaming market. However, these adaptions are done on an ad-hoc basis, the availability and function of these devices are subject to the vagaries of market forces.

Instrumenting the objects used in established tests takes more resources, but it contributes to existing knowledge and faster acceptance of use based on previous ratification. As far we know this is a novel approach.

We seek to use tests that are widely accepted by the industry as they have been ratified through years of deployment. This provides a point of focus and discussion with therapists who would be familiar with the methodology used.

One such test is the Action Research Arm Test (ARAT) formulated by Lyle [2] and further standardized by Yozbatiran et al [3]. ARAT is a performance test designed to assess recovery of upper limb function after damage to the cerebral cortex. It can be used to check on progress in treatment as well as evaluate the effectiveness of treatment. Its administration does not require formal training and it uses simple, short motions which can be scored and completed quickly. The test consists of various objects to be moved in a specified manner, on a table with a raised platform, with the patient seated on a chair. There are other actions as well, that do not involve objects. An assessor will score the quality of the movements, and a total score based on 19 tests provides an overall measure. A useful biomechanical aspect of the ARAT is the hierarchical nature of its assessments. This means that the movements being tested are ranked in order of difficulty in execution. In this instance, they are the Grasp, Grip, Pinch and Gross Movements which involve the fingers. In trying to capture such fine movement, it is difficult to use methods which measure signals attached to the subject as these may impede motion, or in the case of video gives inherently noisy readings and is susceptible to the vagaries of lighting and occlusion effects.

Since we are focussing on the ARAT, it is pertinent to note that it is mainly used for assessing movement disorders caused by stroke. Of the range of movement disorders classified [4], we will look at two. First are involuntary periodic-like muscle movements which come under several categories depending on the intensity of motion, its rapidity and the underlying causes. In this paper we use the generic term *tremor*, which is well understood although the word is more commonly associated with neurological disorders. Second are distorted static hand postures which may be a result of dystonia, which are a type of hypertonia caused by the inability to control the muscle tone. Then there are various degrees and combinations of these movements. Gross tremor frequencies occurring in the movements of the hand were around 1-4 Hz and 6-11 Hz. However, if the hand was weighed down, these frequencies would be reduced [5]. A higher band of frequencies at 15-30 Hz were attributed to finger tremor.

Parnandi [6] describes the automated assessment of stroke patients using the Wolf Motor Function Test (WMFT) [7] detailing how the precision, smoothness and speed of movements may be scored. He uses Inertial Measurement Units (IMU) and motion capture (mocap) cameras to do this. Since the WMFT does not require the patient to handle objects, it requires sensors to be placed on the human body for measurements.

Srinivasan et al. [8] discuss the various ways sensors such as accelerometers embedded into objects used in ADL can help in tele-rehabilitation.

Lee et al. [9] built an earlier prototype of the instrumented device described in this paper which incorporates accelerometers. Portions of their paper have been reproduced here for the sake of continuity in discussion, in particular the sections on hardware and experimental setup and movement disorder types.

The analysis of biomedical signals benefit from decomposition into constituent parts to identify features of interest but care is needed in considering the nature of the signals.

2.1 Signal analysis approaches for assessment

Frequently biomedical signals are nonlinear and nonstationary so that applying Fourier-based decomposition to these signals produce mathematically correct functions, but these may not have any physical meaning at all. These signal constituents serve only to accommodate the lack of linearity and stationarity as explained in [10]. A possible serious consequence is that since various forms of movement disorders are classified based on their intensity and rapidity as mentioned earlier [4], an erroneous diagnosis may result from a frequency that is not physically present! This is a problem with decomposition methods based on basis functions decided *a priori*.

To overcome this, current frequency analyses using data driven decomposition processes have been introduced. Singular Spectrum Analysis (SSA) has been used to analyse naturally occurring physical phenomena and only recently it has been applied to biological signals. The form of the constituent signals it produces are not constrained, for example sinusoids. SSA produces readily interpretable constituent signals from short, noisy signals. Recently, Jarchi et al. [11] analysed various interclass motions using SSA. In contrast, we are analysing intraclass movements.

In our work we combine two types of sensors not often used together, namely accelerometers and force sensors. This has the following benefits: i) it is capable of sensing fine motion and pressure exerted by a person and ii) there is no need to mount sensors on the body of a person. The next section describes our setup.

3 EXPERIMENTAL SETUP

In this section we describe in detail how we implement the ARAT. Our research group perform objective measurements of the ARAT using a variety of sensors. For this paper, we focus on Test1 of the Grasp Subtest which is one of the nineteen in the ARAT suite of movement tests. This test involves the grasping of a wooden block which is 10 cm^3 in size and moving it from a specified point directly to a target. The ARAT specifies this as item 1, but we will refer to this as the Cube in the rest of this paper.

Since our last paper[9], we conducted more extensive pre-trial tests and are in the midst of collecting data from actual patients. A further development besides the set of Intersense 406 FSR resistive sensors for force measurement used earlier in the Cube, was *another* set embedded into a table and a platform as shown in Fig. 2. This includes a sensor built into the backrest of a chair and this new set used for auxiliary measurements. Targets were placed over the sensors in the table assembly. The horizontal distance from the lower sensors to those on the platform was 0.5 m and the sensor on the shelf was 0.25 m from the table as seen in Fig. 2. The sensors were connected as described in the Intersense user manual [12]. Now, two Microchip micrcontrollers were used as Analog to Digital converters as well as data concentrators to transfer data from the two sets of sensors to a workstation via a serial link. The Freescale MMA7260 3-axis accelerometer was used for acceleration measurements in the Cube only and set to a ±1.5g range with a nominal 0.8V/g sensitivity.

The two sets of serial data were streamed into a DTech DT5070 four serial port to USB concentrator which allows a workstation to receive data over virtual serial ports. The sensor readings are taken at a rate of 30 samples/sec so that a maximum frequency of 15 Hz can be reliably recorded which is sufficient for hand tremor, as discussed in Section 2. We used a wired connection for this round of experiments. A block diagram of the entire system is shown in Fig. 1.

3.1 Test subjects and patients

In order to prepare for data collection of patients, we used healthy subjects to characterise normal movements and also to *simulate* movement disorders caused by stroke, which are tremor and dystonia. In this way we are able to compare the movements of a healthy subject and what may happen if they develop movement disorders, which will be very unlikely with patients. We had five healthy subjects and assessed their movements, which will be classified and discussed in the next sub-sections. The four sets of movements are repeated for five times for each person, giving a total of 100 sets of data. The test subjects were briefed as to what constitutes dystonia and tremor and to reproduce them to the best of their ability. Dystonia was simulated by not attempting to keep the Cube upright during movements. Tremors were simulated by stiffening the forearm muscles and attempting to shake the hand, which causes involuntary movement in the hands.

Additionally, we are in the process of collecting data with actual patients who have had a history of stroke and undergone rehabilitation. We perform a preliminary study on two of them. We now briefly describe the possible motions of the Cube in the ARAT as manipulated by a person.

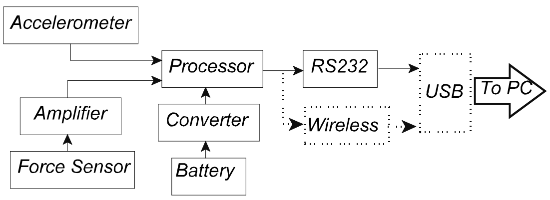

Fig. 1. Hardware block diagram of Cube *and* table/chair embedded sensor system. Dotted lines indicate optional portions.

3.2 Normal grasp and move

In Fig. 2 we see the Cube being grasped by a right handed person moving it from the lower, hand silhouette to the higher black target, the trajectory shown by a broken line. This action has to be completed in a given time. The Cube is held upright and the motion is to be what a healthy person would exert without undue duress. We would expect this task to be completed smoothly, with a minimum of energy. In Fig. 2, note that the non-grasping (left) hand is used as support, so the force exerted on the table can also provide useful data for assessment.

3.3 Skewed grasp and move

In this type of grasp, we consider loss of muscle function that prevents the Cube from being held upright. Rather than use the term tilt, we use SKEW as this denotes a sense of imbalance when executing this type of movement.

3.4 Grasp and move with tremor and/or skew

When the muscles are struggling to keep the Cube in the air, the muscles may tense up and voluntary control is diminished, resulting in tremor. Depending on the nature of the disorder there may also be a skewed grasp on the Cube as well. Thus we have for a subject, four sets of data representing the presence or absence of tremor and/or skewed grasp.

4 SINGULAR SPECTRUM ANALYSIS APPROACH

Singular Spectrum Analysis is a recent subspace analysis method which works best for single channel analysis. SSA easily separates signals out into trends, periodic data and noise. As mentioned in Section 2, SSA decomposes the signals based on its values. The process has two main phases which are subdivided into four steps. In the decomposition step, Singular Value Decomposition (SVD) is used although other methods like Principal Component Analysis and Independent Component Analysis may be incorporated [13]. This is applied to a time series of data $x(i) = \{x(1), x(2),..., x(N)\}$ which has N observations and represented by $\boldsymbol{x}$. We adopt the formulation in [14] which is geared towards signal processing.

Step 1 Decomposition-Embedding
A window of length L is moved over the time series one element at a time to produce a set of vectors

$\boldsymbol{x}_i = [x(i)\ x(i+1)...x(i+N\text{-}L)]^T$ for $i \in Z : i \in \{1,2...L\}$ where ^{T} denotes the transpose operator.

By concatenating all L vectors columnwise, we obtain the trajectory matrix (with a unitary delay)

$$\boldsymbol{X} = [\ \boldsymbol{x}_1\ \boldsymbol{x}_2\ ...\boldsymbol{x}_L\ ] \tag{1}$$

where $\boldsymbol{X}$ is a $N\text{-}L+1$ by L matrix and is also known as a Hankel matrix with its anti-diagonals having the same value.

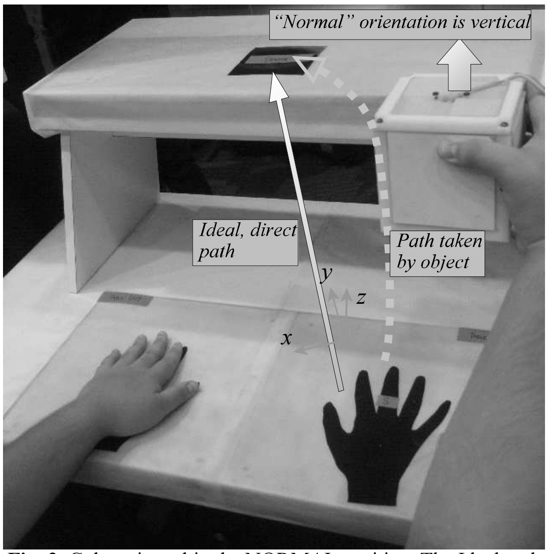

Fig. 2. Cube oriented in the NORMAL position. The Ideal path of object, compared to actual path taken is shown. Left hand is placed on the table sensor and used as support. Two sets of force sensors are used, one in the Cube, and another in the table assembly.

Step 2 Decomposition-Singular Value
Using SVD on $\boldsymbol{X}$, the sorted eigenvalues and right singular eigenvectors of $\boldsymbol{X}^T\boldsymbol{X}$ respectively λ_i and $\boldsymbol{v}_i$ are computed, together with $\boldsymbol{u}_i$ which are the left singular eigenvectors - of $\boldsymbol{X}\boldsymbol{X}^T$.

Step 3 Reconstruction
By standard linear algebra, $\boldsymbol{X}$ can be reconstituted by:

$$\boldsymbol{X} = \sum_{i=1}^{L} \sqrt{\lambda_i}\boldsymbol{u}_i\ \boldsymbol{v}_i^T$$

where each $\sqrt{\lambda_i}\boldsymbol{u}_i\ \boldsymbol{v}_i^T$ is called an eigentriple and is a rank-1 matrix.

Step 4 Reconstruction- Diagonal averaging
To obtain a reconstructed time series $\hat{\boldsymbol{x}}_i$ which is an approximation to the original $\boldsymbol{x}_i$, we may express the procedure in the following form:

$$\hat{\boldsymbol{x}}_i = \boldsymbol{D}^{-1}\ \boldsymbol{Y}^i\ \boldsymbol{v}_i$$

where the diagonal $N \times N$ matrix $\boldsymbol{D}$ has as its elements a series of integers $d_{ii} \in Z : ii \in \{1,2...L\}\ \{L,N-2*(L+1)\}\ \{L...,2,1\}$ and the matrix $\boldsymbol{Y}^i$ is formed as in (1) from an auxiliary time series $\boldsymbol{y}_i$ of length N consisting of the eigenvector $\boldsymbol{u}_i$ padded with zeros

$$y_i(t) = \{u_i(1),\ u_i(2),...,\ u_i(N-L+1)\}\ \{0,L\} \text{ and}$$

$$\boldsymbol{Y}_i = [\ \boldsymbol{y}_i^1\ \boldsymbol{y}_i^2\ ...\boldsymbol{y}_i^L\ ]$$

where $\boldsymbol{y}_i^1 = [u_i(1), u_i(2),..., u_i(N-L+1)\}\{0,L\}]^T$
$\mathbf{y}_i^2 = [0\ u_i(1), u_i(2),..., u_i(N-L+1)\}\{0,L-1\}]^T$ and so on.

In concatenating the vectors $\boldsymbol{y}_i$, it can be seen that $\boldsymbol{Y}_i$ is a Toeplitz matrix. This procedure gives a reconstructed signal $\hat{\boldsymbol{x}}_i$ corresponding to the *ranked* eigenvalue λ_i and indicates the amount of contribution of $\hat{\boldsymbol{x}}_i$ to the original signal. In many instances, various $\hat{\boldsymbol{x}}_i$ can be grouped together for analysis.

5 RESULTS

Here we discuss some initial results and show how the design of the sensors help us to interpret the readings obtained. This is followed by an analysis of the smoothness of movement.

5.1 Qualitative results

In Fig. 3 we show the waveforms obtained for a SKEW movement. They yield detailed insights into the assessment which we believe cannot be obtained in any other way. First is that a patient may *drop* the Cube, by releasing it before placing it on the upper table. This is shown in Fig. 3 where we note that contact was made with the bottom face *before* the Cube was released. Second is that the grasped surface shows peaks when just picked up and just before releasing. The peaks show concentration on the task performed and describes what Flatt [15] refers to as the "power" grasp. However once the Cube is firmly grasped, the transport phase uses the "precision" grasp which does not use so much force. Note that at the start time of data capture and considering the force plot, the lines with 'x' and '.' markers have values that are close to zero. These are the surfaces which the hand will grasp. The non-marker line represents the force exerted by the weight of the Cube as it rests on a surface.

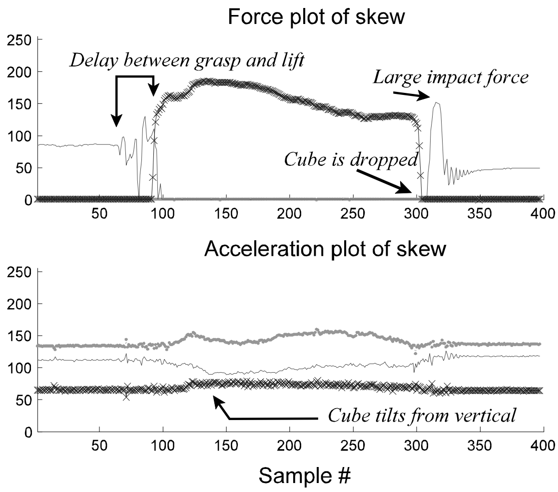

Fig. 3. Skew motion - note the force plot where the cube is dropped rather than placed in the top plot. In the lower plot, the tilt from the vertical is indicated.

Thirdly, the signals given by the bottom sensor was also very useful in acting as a cue as to when the Cube was lifted which signalled the start of a movement and also when it ends. While this was clear cut for the healthy subjects, some of the patients had problems disengaging the Cube from their grasp at the end of the move. These extraneous signals were easily detected and removed in the course of analysis using this cue. Fourthly, an important result was that since the ARAT is a timed test, the period when the Cube is lifted can be automatically and precisely measured, and used as part of the of an assessment.

5.2 Computational results

In the course of our earlier work [9], we resorted to using frequency domain measures with a measure of success in an early prototype of the Cube in a limited experiment. However, with more data, this approach did not yield good results with the spectrum becoming very cluttered.

In resorting to using SSA on the accelerometer signals in Fig 4, we note the reconstructed components of the first five largest eigentriples have nicely discernible waveforms in the right column, even if the original signals in the left column are somewhat noisy. We used a window size of 28 to accommodate the shortest time series in our dataset although the average length of the time series was about 50, which corresponds to a movement time of around 1.65 seconds at a sample period of 33 milliseconds.

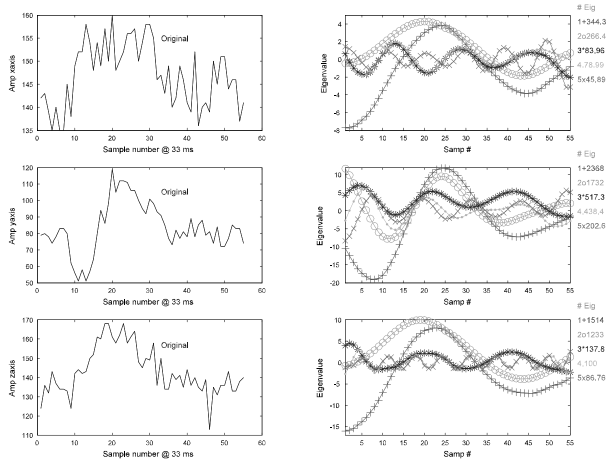

Fig. 4. Plots of accelerometer outputs of a healthy subject in the *xyz* directions in the left column. Right column has plots of the reconstructed signals using the first 5 eigenvalues for each of the accelerometer outputs. The y-axis is vertical.

In SSA decomposition, the noisy part of the waveforms are consigned to higher eigentriples which are not shown here. Next, in Fig. 5 we show a comparison plot between that of a healthy patient simulating a move with tremor and skew in the left column and that of an actual patient on the right column.

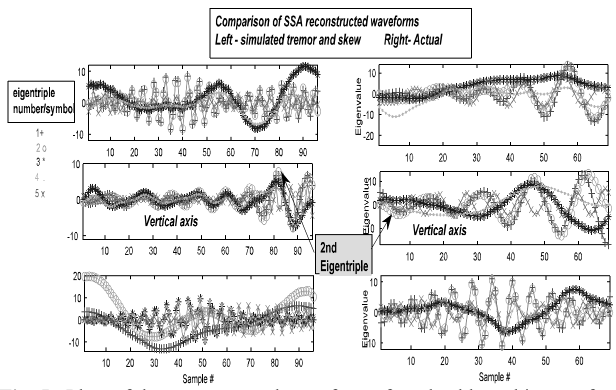

Fig. 5. Plots of the reconstructed waveforms for a healthy subject performing a tremor and skew movement compared with that of an actual patient on the right.

We observe that in the second plot which represents the *y* or vertical axis, and the *second* eigentriple, marked with a green 'o' gives a good indication of the tremor movement. We denote this signal as *Y2* and note that it is a smoother waveform and thus would produce less spectral artifacts. This is an application of SSA for data smoothing. As an exploratory step, we perform an analysis on *Y2* in the following way:

i) remove Direct Current (DC) components of 0 Hz
ii) perform a Fourier Transform
iii) sort the amplitudes
iv) select the frequency corresponding to highest amplitude
v) for each subject, partition the data into those with and without tremor
v) remove 10% of the outliers
vi) obtain the mean frequency for both classes of movement

The outlier removal step comes about because of the variability in the execution of the simulated moves. We used a figure of 10% for removal as a reasonable rule of thumb. In Table 1, we show a portion of the results. The Trial ID is formulated as *SN_MM_T* where *S* is H/P for healthy subject and patient respectively, *MM* is the movement type, NM for Normal, TS for Tremor and Skew (other two not shown) and *T* is the trial number, 1 to 5.

Table 1 The frequencies corresponding to the components with the largest amplitude for the eigentriple *Y2* of the selected trials.

Trial ID	Frequency of largest amplitude of *YF2* (Hz)
H1_NM_1	1.13
H2_SK_1	0.88
H3_TR_1	6.11
H4_TS_5	6.84
P1_TS_1	2.24
P1_TS_2	1.18
P2_TS_1	1.45
P2_TS_1	1.85

In considering the entire data set, we are able to obtain a mean frequency of 1.1 Hz with a standard deviation of 0.5 for the movements without tremor, namely the NORMAL and SKEW moves and 4.1 Hz and a deviation of 2.4 for those with tremor which are the TREMOR and TREMOR/SKEW moves. This may be interpreted that as healthy people perform normal movements, they are generally smoothly executed. However with simulated tremor, the execution of the motion requirement is subject to interpretation and thus can vary. In any case, with this information, we can see that except for *P1_TS_2*, stroke patients have a borderline tremor condition when moving the Cube.

6 CONCLUSIONS

In summary, we have put the case for instrumented objects to be used in standard assessments in rehabilitation in Sec. 2. The benefits were shown in the greatly enhanced information obtained from force sensors about a person's grasp and motion in four ways viz., being able to distinguish the various phases of a movement, the difference between placing and dropping an object, often by scant milliseconds and precisely demarcating the relevant portions of data in a trial and thereby its duration.

In highlighting the pitfalls of using data decomposition methods using predetermined basis functions, we saw that SSA produces readily interpretable results which can *then* use traditional analyses. Exploratory analyses indicate that using one axis of an accelerometer, we can detect some tremor in patients.

Future work will involve tridimensional analyses, analyses of SKEW and incorporation of force data for a more robust determination and characterisation of movement disorders as well as comparison with other signal analysis approaches.

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