Effect of Impairment on Upper Limb Performance in an Ageing Sample Population

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Abstract. Ageing and age-related impairments have a detrimental effect on human performance and are likely to affect gesture based Human-Computer Interaction (HCI). Relying on "healthy" individuals to define gestures used for interfacing is likely to bias HCI design within the older population. To what extent gestures are affected by a common ageing disease remains to be determined. The aim of this study is to explore spatial and temporal changes in shoulder motion between rotator cuff patients and "healthy" controls. Seven controls and eight pre-operative patients participated in this study and performed several predefined gestures. The results show that the ROM and speed of movement can be affected by a common age-related disease. Wavelet analysis indicated that patients have a higher level of coupling between conditions making it harder to differentiate between different gestures. These results highlight the need to include age-related disabilities in HCI study populations.

Keywords: Human Gesture, Pattern Recognition, Ageing, Rotator Cuff Injury, Wavelet Analysis.

1 Introduction

Gesture recognition has changed Human-Computer Interaction (HCI). In the last decade, interaction with electronic equipment has moved towards more natural and unobtrusive ways of interfacing. There has been a shift from artificial small gestures to larger everyday movements. Commercial tracking systems have now reached a stage where they are capable of providing accurate information for sensitive motion tracking [1]. However, the growing popularity of using 3D human movement for device control also requires the users to have a certain level of ability. Individuals who have limited ability might not be able to benefit fully from an ever increasing diversity of control gestures. Currently, the algorithms for gesture recognition are often optimized for "healthy" individuals. Specific designs are needed to cater to those who are less able to perform certain movement trajectories [2]. A good understanding of impaired

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human performance is therefore needed. Performance parameters, such as movement velocity, can be used to better discriminate between young and older subjects [3]. Gait speed itself has been found to be a good predictor of mortality [4]. This shows that ageing has a detrimental effect on maximum overall performance. Research has now started to take ageing into account when looking at HCI [5]. However, the changing interactions during ageing are further complicated by disease. This can put the older person who suffers from an age-related disease in a position where they can no longer interact with gesture controlled devices. This is particularly relevant if new gesture parameters, such as movement velocity, are introduced. Gesture speeds can be accurately identified across ordinal scales, such as “slow” and “fast”[6]. Yet, these classifications are tested with “healthy” subjects. This paper aims to investigate the summation of ageing and disease upon performance of the upper limb in order to inform interfacing paradigms for gesture led control.

The focus of this study will be on rotator cuff injury, as rotator cuff tears are among the most common conditions affecting the ageing shoulder [7]. The rotator cuff consists of four muscle-tendon units that move the shoulder joint. They are particular important for reaching maximum shoulder rotations and damage can subsequently minimize the volume of space through which the arm can travel. The large range of motion that is available for the shoulder complex requires a multitude of different joints to be coordinated in a stable manner. The trade-off between operational volume and stability puts a great strain on the rotator cuff. Functional shoulder measurements that are currently used clinically often test an average level of system performance at a single comfortable speed. Increasing speed during shoulder activities might disperse patient groups that initially seemed similar. How the potential for making specific gestures changes across speeds remains unclear.

The aim of this study is to explore spatial and temporal changes in shoulder motion, in both healthy asymptomatic healthy adults and rotator cuff patients, during different speeds of movement.

2 Methods

2.1 Participants

Seven healthy control participants and eight pre-operative patients voluntarily participated in this study. Relevant demographic data of each group is given in Table 1. The protocol was approved by the College Research Ethics Committee. All subjects gave written informed consent before the experiment.

Table 1. Mean (± standard deviation) values for the demographics of all subjects. No significant differences were present between groups as tested with an independent t-test.

	Age (yrs)	*Height (m)*	*Mass (kg)*
Controls	41±18	1.75±0.04	82±11
Patients	53±10	1.74±0.03	81±10

2.2 Tasks

Participants were asked to move the arm in several predetermined motion patterns at normal and fast speeds. Five range of motion (ROM) tasks were actively performed by the subjects. The active ROM tasks were measured at a self-selected speed, as well as during the maximum speed the patient was capable (or willing) to perform. These two conditions will be referenced as the "normal" and "fast" movement speed condition. Participants were allowed to practice the movements to ensure that they understood in which plane the movement needed to be performed.

The ROM tasks consisted of elevation in the sagittal (forward flexion), scapular and frontal (abduction) plane (Fig 1). Participants were also asked to perform axial rotation consisting of external and internal rotation of the arm during 90 degrees of abduction.

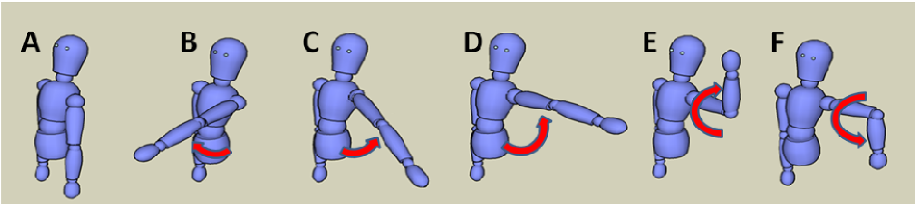

Fig. 1. Movements performed by participants. (**A**) Starting position for each movement. (**B**) sagittal (forward flexion) plane rotation (**C**) scapular plane rotation (**D**) frontal (abduction) plane rotation (**E**) external rotation and (**F**) internal rotation.

Subjects were instructed to reach a maximal joint angle in each active ROM task. Participants were asked to repeat each task three times.

2.3 Materials

Motion tracking was performed using an active motion analysis system (Codamotion, Charnwood Dynamics, Leicestershire, UK) to accurately measure the three-dimensional position of the upper extremity. Markers were placed on the thorax, humerus and scapula. The following marker positions were used for digitization of the shoulder; origin of brachoradialis, biceps belly, insertion of deltoid, acromion (marker placed on the acromioclavicular joint), and the short, medium and long stem of a scapula tracker. Double-sided adhesive tape was used to fix each marker to the skin. Local coordinate systems and segments were constructed from bony landmarks and marker positions as defined by the UK National Shoulder Model [8]. A functional (rather than geometrical) method relying on linear regression was used to define the centre of rotation for the glenohumeral joint [9]. Joint angles were defined based on the International Society of Biomechanics standardization proposal of the International Shoulder Group [10].

Since dynamic tracking of the shoulder blade is difficult (due to its movement under the skin), measurements were performed using a new procedure that relates the scapula motion to that of a skin-fixed scapular tracker [11]. The tracker consists of a base with a groove in it that allows it to conform to the subject's scapular spine, and an adjustable 'foot' that is positioned over, and then attached to, the posterior-medial aspect of the acromion process (Fig 2). This technique has been validated, but errors due to skin motions are still possible, leading to measurement errors of less than 5° [12].

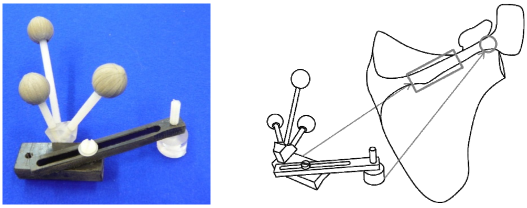

Fig. 2. Scapular tracking device used for measuring scapula (shoulder blade) movement

The selected joint angles were obtained between the humerus and scapula segments. All further data analysis, subsequent to data collection, was done in Matlab (MathWorks, Inc., Natick, MA, USA).

2.4 Statistical Analysis

Range of motion and mean angular velocities are compared between groups (controls and patients) and conditions ("normal" and "fast" speed of movement). A one-way ANOVA with a Bonferroni's multiple comparison test was used for statistical analysis, as normality was assumed based on obtained histograms.

Movement data within subjects was also analyzed using wavelet coherence. The wavelet coherence can be interpreted, to some extent, as a measure of local correlation [13] and provides a valuable method to analyze the frequency content over time. This technique can be used to assess how the signal differs between the "normal" and "fast" condition within a group. Signals were aligned at the starting point of movement using a threshold value algorithm that identified the alignment point of the movement, as defined by the first crossing of the 10% value of the maximum ROM.

2.5 Wavelet Analysis

Physiological signals vary in time, subsequently allowing for the application of a Fourier analysis, which relies on adding together the appropriate potentially infinite sum of sine waves. However, most behavioral signals are not infinite and require the detection of localized features. For movement the use of wavelets would be more appropriate. Wavelets are functions that are localized in both physical space and wave-number space, contrasting the Fourier transform that is based on functions (sines and cosines) that are well localized in wave-number space, but not in the physical space [14]. A wavelet is a special case of a vector in a separable Hilbert space that generates a basis under the action of a collection of unitary operators defined in terms of translation and dilation operations [15]. We use a continuous wavelet transform

(CWT) to divide the signal into wavelets, allowing us to analyze the frequency content over time. This information can then be used to compare two signals and find a potential relationship between them. Regions where the signals have equal power or phase behaviour indicate an association. Data was analyzed with Matlab's wavelet toolbox (MathWorks, Inc., Natick, MA, USA).

A bi-orthogonal Gaussian waveform was selected for the wavelet analysis, as it was expected to show the best match with the performed activities. The wavelet coherence of two time series x and y can be described as,

$$\frac{S(C_x^*(a,b)C_y(a,b))}{\sqrt{S|C_x(a,b)|^2}\sqrt{S|C_y(a,b)|^2}} \tag{1}$$

where S is the smoothing operator, while $C_x(a,b)$ and $C_y(a,b)$ denote the continuous wavelet transforms of the "normal" signal x and the "fast" signal y at the scales a and the positions b.

Two examples of simulated outcomes for wavelet coherence are given in Fig. 3. These examples show the wavelet coherence of two generated sine waves, which mimic the "fast" and "normal" condition. In one example (A.1) there is a factor 2 difference in movement frequency between the conditions, while the second example (A.2) shows a very small offset from the baseline frequency. It is clear from Fig 3 that there are more localized similarities in B.2 compared to B.1.

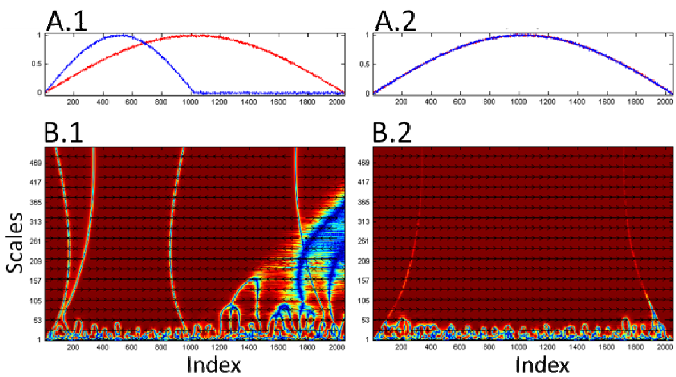

Fig. 3. Example of wavelet coherence based on two waves with different frequencies. **A.1** The red signal shows a sine wave with a frequency f, while the blue trace has a frequency of 2f. Zero-mean Gaussian noise is added to both signals. **A.2** The red signal shows a sine wave with a frequency f and the blue trace has a frequency of 1.001f. Zero-mean Gaussian noise is added to both signals. **B.1/B.2** The heat map shows the modulus, wherein dark red represents 1 and dark blue 0. Small arrows are used to represent the relative phase between the two signals.

A visual representation of localized similarities between the "fast" and "slow" condition within a group can be obtained by superimposing all wavelet coherence graphs. This procedure will be performed for the frontal plane, as this plane is essential in both 2D and 3D gesture recognition. All data was normalized for each subject to both maximum amplitude and duration. This normalization allowed for comparison of the relative similarities in patterns for the "normal" and "fast" conditions.

3 Results

3.1 Range of Motion

The glenohumeral shoulder joint range of motion (ROM) showed significant differences between control subjects and patients across all elevations at "normal" speed (Fig. 4). The greatest difference between groups was found for sagittal elevation, with a mean difference of 40° (p<0.01). By increasing the speed of movement this difference was brought back to 33° (p<0.05). Frontal elevation range of motion showed a non significant decrease between groups when motion was voluntarily speeded up (37° [p<0.05] for "normal" vs 33° for "fast"). However, increasing rate of motion only further increased differences in the scapular plane. Scapular elevation difference changed from 30° (p<0.05) during the "normal" speed to 35° (p<0.01) for the fast condition. No significant difference was found in axial rotation between groups. No significant within group differences were found across all tasks.

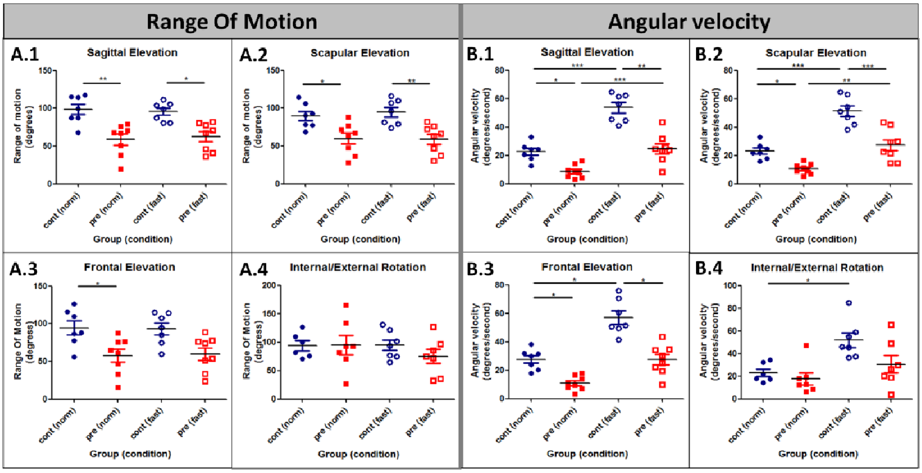

Fig. 4. Maximum range of glenohumeral motion (**A**) and mean angular velocity (**B**) at the shoulder joint. Control group data is shown as blue circles and patient data is represented by red squares. Filled circles or squares give data at "normal" speeds, while open circles and squares relate to the "fast" speeds. Cont=controls, pre=pre-operative patients, normal=normal movement speed, fast=fast movement speed. Asterisks indicate significant difference between groups or conditions. * = p<0.05, ** = p<0.01 and *** = p<0.001.

3.2 Angular Velocity

Higher angular velocities (p<0.05) were found for controls compared to patients across all elevations. This difference between groups became greater when participants were asked to increase the movement speed. The most significant difference between groups was found for scapular elevation during the "fast" movements, with a difference of 24°/s. No significant difference between groups was found for the internal/external rotation activity.

Angular velocity data showed that both subject groups speed up their movements during the "fast" condition when compared to the "normal" condition. However, the controls significantly increased velocity across all tasks when asked to go "fast", while significant differences in angular velocity in patients were only present for the sagittal and scapular elevation.

3.3 Wavelet Coherence

Determining the wavelet coherence and superimposing the phase of the smoothed wavelet cross spectrum shows that data from the two conditions often exhibited coherence near 1 for the majority of the signal in the frontal plane, as well as showing an approximately constant relative phase at the scales of interest (Fig 5.).

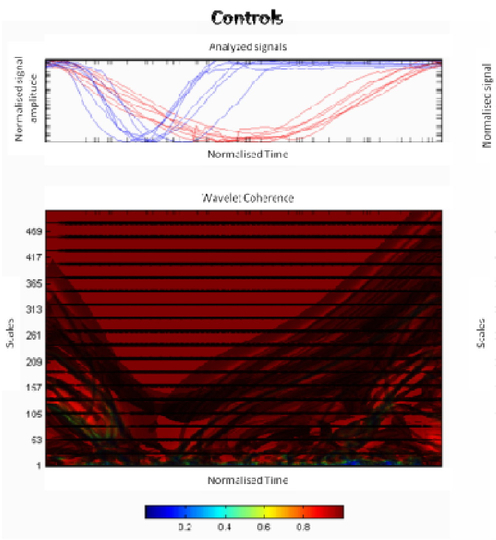

Fig. 5. Wavelet coherence of all subjects during elevation in the frontal plane. Top two plots show all the traces for the "fast" (blue) and "normal" (red) condition for both groups. Time was normalized to the start of the "normal" movement till the end of the motion pattern. Signals were normalized to maximum amplitude measured within a subject. Bottom two plots show the overlap of modulus and relative phase changes. The non-linear patterns indicate the occurrence of large relative phase shifts.

There is a relative phase shift across the scales when the modulus becomes zero. These shifts are mainly seen at the lower normalized scales (higher frequencies). The lower normalized frequencies of (<3Hz) start at scale 93 and is represented by the top 82% of the wavelet coherence plot. Several variations in the relative phase shift within the lower frequencies can be observed between participants of both groups. However, the wavelet coherence patterns from the control group provide a more ordered arrangement than that of the patient group.

4 Discussion

The aim of this study was to explore changes in shoulder motion during different speeds of movement for both healthy asymptomatic older adults and rotator cuff patients. The results show that the available ROM is not affected by the velocity at which a particular task is performed. However, ROM is affected by musculoskeletal damage. A decrease of up to 40 degrees was found in the elevation tasks when control subjects were compared to patients. The difference found in this study between patients and controls matched those reported in the literature [16]. The peak rotations related to the available volume in which gestures can be performed. The diminished ability to lift or rotate the arm will drastically reduce the gesture workspace.

In addition to a change in movement range, changes in angular velocity were also found. As expected the angular velocities were greater in the "fast" condition compared to the "normal" condition. Control subjects showed a higher rotation velocity during the "normal" conditions, but also managed to produce a greater increase when switching to the "fast" condition compared to patients. Although, no significant difference was found for the internal/external rotation activity a trend towards a greater group differentiation at the faster condition was still present. This difference in ability of an older age group that is affected by a disease shows the need to include them in reference databases that are aimed to inform gesture led control.

The wavelet coherence analysis showed that patients have a greater variance in localised features than controls. The power of such an analysis lies in the ability to detect short episodes of coherence within single measurements, which would not be possible using classic Fourier-based coherence [17]. It can be observed that some patients compensate well for the musculoskeletal damage, while the abilities of others are diminished. This suggests that there are subgroups within the patient population.

The normalization procedure generates relative patterns that can be compared between subjects. Subsequently, dissimilarities between these patterns relate to relative differences in amplitudes and times. On average the patient group showed a greater coupling of the "fast" and "slow" condition, in addition to a higher overall variance, this indicates more inconsistency for the estimators of gestures. Differentiation between gestures is therefore harder to accomplish for the patient group independent of the range of motion reached or the angular velocity at which the movement is performed. This demonstrates a more fundamental gesture generation difference between healthy and impaired individuals that goes beyond the level of range or speed. Gesture recognition depends on a consistent difference between two or more gestures, but increasing the range of motion and angular velocity of patients does not automatically bring the patient group in line with the controls. The greater difference in localised features highlights the need to include common disabilities in the HCI design for the older population, as the movement patterns are different across dimensions.

The research presented here is conducted within a laboratory setting. It is known that differences in ecological validity exist between lab-based results and those obtained during real-world interaction. Laboratory testing can be somewhat artificial and divorced from real-world interaction [5]. The study presented here focuses on what happens with motor performance when disease impacts on ageing. However, the purpose is not to generate a generic guideline for the selection of participants in HCI design studies. It aims to inform the field of potential biases that arise by ignoring age-associated diseases when designing for an older population.

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