Arm movement: The effect of obesity on active lifestyles

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Abstract

Triaxial accelerometer logging using a sensor located in an arm band positioned immediately above the elbow was used to record the active range of motion, arm elevation angles and speed of movement activities throughout the waking hours. Using a 10 Hz sampling speed, the position of the arm was recorded in four angular position zones include at rest, the elbow is raised to within $\theta$ degrees of the horizontal, the elbow lies in the range $\pm \theta$ degrees of the horizontal, and the elbow is higher than the shoulder by more than $\theta$ degrees. A graphical user interface (GUI) was developed to determine the time spent in each zone and the transition speed through the zones. Working women aged over 30 years old volunteered for this study. The participants were divided into groups and wore the armbands during the waking hours. There is statistical evidence that the angular velocity is linearly related to multiple variables such as body mass index and age ($r = 0.75$).

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1. Introduction

Obese humans tend to minimise movement including movements of the arm. The effect of obesity on range, velocity and acceleration of movements of the upper limb has not been investigated. As whole-body obesity is strongly associated with decreased physical activity [1], it may also contribute to reduced quantity and quality of limb movements and so reduced participation in sport and exercise. The first step in understanding the effect of obesity is to look at how people move in normal activities. The aim of this study is to compare the quantity and quality of upper limb movements in women with Body Mass Index

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(BMI) over 25 kg/cm² classified as obese according to the World Health Organization (WHO) 2004 with those of BMI < 25. Almost all human movement activities require arm movements – either for the activity itself (e.g. lifting objects, eating, bathing, brushing teeth etc or playing sports such as tennis, hockey, cricket, swimming, etc.) or for balance (e.g. walking, running or playing foot sports such as soccer). For this reason, measurements of the upper arm imply shoulder action which in-turn, indicate activity levels. Shoulder injuries are a major problem in many sporting codes [2]. A number of factors may contribute to injuries, including dyscontrol of movement [3], weakness of muscles about the shoulder and decreased range of motion at the shoulder. All three aspects may be present in obese persons. Post-operative care for patients with shoulder injuries requires the patient to undertake mild arm exercise. Similarly post-operative breast cancer patients are encouraged to perform similar mild levels of exercise. Simple reliable methods of recording arm movements over long periods is highly desirable.

This paper reports a preliminary investigation into the use of three axis accelerometer sensors to monitor the daily living activities of small cohort women. The population was selected to cover a wide range of BMI values. The objective of the study was to assess the position of the arm in the relaxed state and then to record arm movements over a long period of time during daily activities.

Portable triaxial accelerometer sensors have been used to monitor human movement [4]. The sensors respond to movement (linear acceleration, angular velocity and angular acceleration), but when the movement is slow or non-existent, the sensors record the gravitational acceleration. During daily living when the subject is not engaged in exercise, the acceleration due to motion can be ignored and the angular position of the sensor to the vertical (i.e. gravity) can be determined. If the measurements exceed 1 g (i.e. are greater than the gravitational acceleration) then movement must be the cause. It is on this basis that the position of the elbow relative to the shoulder can be inferred. If the elbow is unsupported one can infer that muscle action is required.

If the elbow is supported (e.g. resting on an elevated platform) no muscle action is involved. Similarly when the subject is reclining, the elbow might be approximately the same elevation as the shoulder. In these (common) situations, then data from the accelerometer can be misleading. These errors can be mitigated by reviewing the period of time spent in such positions. It is unlikely that a standing subject will maintain a horizontal arm position of a long period of time. Similarly a prone subject is unlikely to rapidly change from their prone position to a vertical position. Thus some of these uncertainties can be deduced from an investigation of the accelerometer record.

The goal of this current research project was to assess the equipment and interpretation software for long time period studies of this type. The quantity and quality of upper limb movements in women whose BMI is in the ‘normal range’ (BMI < 25) with women who are obese (BMI > 25) was compared.

2. Methods

2.1. Technology

The sensors used for this experiment were the in-house generic monitoring platform design n-core [5]. This platform contains two embedded accelerometers each of which is capable of measuring acceleration forces of ±10g in two perpendicular directions. This enables collection of data in a three dimensional space. The n-core reports a static 1g response due to gravity when oriented vertically.

The units were placed on the upper arm with the +x axis directed to the top of the shoulder (Figure 1). When the person has the arms relaxed by their sides, the x axis records -g and both y and z axis are zero. The x axis is the only axis that contributes to the movement from -g (resting arm) to +g (arm above the shoulder), and for that reason, it was the only axis extracted and processed.
Fig. 1. n-core unit (n) placed on the outside of the upper arm, with the -x axis directed to the elbow recording -1g when the arm is relaxed by its side.

The n-core unit was used to record the active range of motion, arm elevation angles and speed of movement activities throughout the daily waking hours. Using a 10Hz sampling speed, the position of the arm was recorded in four angular position zones:

- Zone 1: The arm is resting by the side at an angle ($\alpha$)
- Zone 2: The elbow is raised to within $\beta$ degrees of the horizontal
- Zone 3: The elbow lies in the range $\pm \beta$ degrees of the horizontal
- Zone 4: The elbow is higher than the shoulder by more than $\beta$ degrees

where $\beta$ (angle size) is an input parameter measured above and below the horizontal axis when $x = 0$.

2.2. Participant selection

This study has been approved by the Human Research Ethics Committee of the University of Sydney (Ref. No. 14943), and all the participants granted informed consent before commencing the study. Working women ($n = 15$), aged between 30-60 years old, in good general health were enrolled in this study. In addition to the quantitative data collection from the n-core sensors demographic characteristics, medical history, current medication and arm dominance were recorded. All the physical measurements were undertaken in a single session by a trained assessor. The stretched stature and weight were measured and BMI was calculated from those measurements. The qualitative data collection contributes to the accurate analysis of the data extracted from the sensors.

The interest of this study is to know and record what daily activities or exercise habits the participants have, so they were required to wear the sensors for one full day, placing them in the morning and removing them before going to bed. Each participant wore two sensors placed on right and left arms.

2.3. Sensor calibration

All participants were instructed on how to use the basic controls of the n-core. They placed the sensor by themselves using a provided fabric armband fitted with Velcro around the upper arm, and were required to record the start time and stop time. For the calibration process, once the participants placed the sensor, they were required to perform the following actions: 1) After the armband is placed on the upper arm, stand motionless with the arms relaxed by your sides for 20 seconds. 2) Bring your arms to the horizontal position at shoulder level for 5 seconds. 3) Return your arms to the relaxed by your sides for 20 seconds again.

The calibration process allows the software to automatically detect the resting angle ($\alpha$) from Zone 1 (subsection 2.1) as $\alpha = \sin^{-1}(\bar{X}_c / g)$, where $\bar{X}_c$ corresponds to the mean value of the motionless 40 seconds
from steps 1 and 3 of sensor calibration, and \( g \) corresponds to the gravity \((9.8 \text{ m/s}^2)\). The resting angle is then used for the measurements on Zone 1 and the transition to Zone 2.

**3. Graphical user interface**

A graphical user interface (GUI) was developed for the semi-automatic analysis of the sensor data. It was developed using an auto generation GUI tool in Matlab environment [6]. The GUI offers a visual record of the time spent in each one of the four zones and the transition speed through the zones.

The data from the sensors is downloaded as a text file and then read by the GUI interface for the pre-processing, filtering (using a *running mean filter*) and post-processing. The results can be visualized through the following options:

- Percentage of time the elbow is within each of the 4 zones.
- Total time (HH:MM) the elbow is within each of the 4 zones.
- Number of times the arm is lifted to zones 2, 3 and 4.
- Histogram of the angular velocity that shows the transition speed from \(-\beta\) degrees to \(\beta\) degrees from the horizontal (axis \(x = 0\)).

**4. Results**

Two individual case studies are presented in this section. The first includes the comparison of the four points described in Section 3, between two right-handed female participants with different BMI and with the sensors placed in their right arm. The second summarizes the data obtained from all participants. Table 1 includes the physical description of the two participants, together with the processing parameters such as time on/off, angle \(\beta\) measured from the horizontal (axis \(x = 0\)), filter length and resting angle \(\alpha\).

| Participant | Age | Weight | Height | BMI   | Time on | Time off | \(\beta\) | Filter length | \(\alpha\) |
|-------------|-----|--------|--------|-------|---------|----------|---------|---------------|---------|
| 1           | 43  | 49kg   | 1.58m  | 19.63 | 7:00am | 7:30pm   | 20°     | 15            | -74°    |
| 2           | 53  | 100kg  | 1.70m  | 34.60 | 11:00am| 11:30pm  | 20°     | 15            | -67°    |

Both female participants recorded approximately 12 hours of common daily activities. Figures 2a and 2b show the filtered data with an indication of the number of points that fell into each of four categories: (a) points \(>+\beta\), (b) points \(\pm\beta\), (c) \(\alpha<\) points \(<-\beta\) and (d) points \(<\alpha\). Categories \(a\), \(b\) and \(c\) measure \(\beta\) with respect to the horizontal. Category \(d\) refers to the points less than the resting angle \(\alpha\), which may be considered as the points related to the movement of the arm to the back of the body (walking). These points were added to the \(c\) measurements since they do not contribute to the arm lifting energy expenditure and can be considered as resting points.

Tables 2 and 3 summarize the percentage of time (%), total time (HH:MM) and number of times per hour the arm is lifted over the four categories described previously. Both participants recorded the highest percentage of time when the elbow is \(\alpha\) and \(<-\beta\). Both spent less than 1% of the total time with the arm above the shoulder. Participant 2, due to her high BMI, lifted the arm above the shoulder only quarter of the time of participant 1. As can be seen in Figure 2a, participant 1 has a concentration of time above the shoulder at the beginning of the day, suggesting that some exercise was performed. However, the same figure shows that only few times in approximately 4 hours, the arm was lifted at \(\pm\beta\) and none at \(>+\beta\), suggesting that computer work was performed. Participant 2 spent twice the time at resting position.
Fig. 2. Filtered data with an indication of the points at categories: points > +β, points ±β, α < points < -β and points < α, where α is the resting angle (a) Participant 1 (b) Participant 2.

Table 2. Percentage of time (%) and total time (HH:MM) the elbow is at every position zone.

| Participant | α   | < -β | ±β  | > +β | α   | < -β | ±β  | > +β |
|-------------|-----|------|-----|------|-----|------|-----|------|
| 1           | 21.03 | 74.05 | 3.50 | 0.84 | 02:35 | 09:27 | 00:25 | 00:06 |
| 2           | 32.20 | 65.05 | 1.89 | 0.46 | 04:03 | 08:11 | 00:14 | 00:03 |

Table 3. Number of times per hour the arm is lifted above the resting angle (α) and the angle size (β).

| Participant | > α | > -β | > +β |
|-------------|-----|------|------|
| 1           | 360 | 40   | 13   |
| 2           | 243 | 22   | 3    |

Figure 3 shows the histogram of the angular velocity for participants 1 (P1) and 2 (P2), on transitions from ±β to > +β. The mean and standard deviation for P1 are 0.0875 and 0.0376, respectively, while for P2 are 0.0417 and 0.0278, respectively. P2 recorded half of the transition speed compared to P1, which lifted her arm almost three times as often as P2. A t-test was performed for both angular velocity vectors and it was found that the two populations of angular velocity are statistically different for the two participants (p < 0.01).

For the second case study, 15 female and right-handed participants were considered in the ranges of 30 to 60 years old, 50 to 100kg, 1.50 to 1.80m and 19 to 39 BMI. Tables 1 to 3 were filled with the respective information of each participant. Multiple correlation analysis (r) was performed for the two variables (BMI and age) and the number of times (m) per hour each participant lifted the arm at (aa) α < m < -β, (bb) -β < m < +β and (cc) m > +β. A strong positive correlation coefficient (r = 0.81) at aa. The correlation coefficients for bb and cc were r = 0.63 and r = 0.55, respectively. The moderate correlations at bb and cc may be related to the fact that the arm was lifted fewer number of times at those positions by all participants. The number of samples was much lower than aa, (see Table 3 for two participants and the pink trend of Figure 2). There is also statistical evidence that the multiple variables BMI and age are linearly correlated to the mean of the angular velocity (r = 0.75).
5. Conclusions

A comparison between women whose body mass index is in the ‘normal range’ (BMI < 25) with women who are obese (BMI > 25) was presented in this paper. Triaxial accelerometer logging using a sensor located in the upper arm was used to record the active range of motion, arm elevation angles and speed of movement activities throughout the waking hours. A reduced number of times the arm was lifted at different categories and a slow movement between transition zones were found in women with BMI > 25. A strong positive trend was found for the angular velocity and the number of times per hour the arm was lifted between the resting angle and -20º of the horizontal, as a function of the multiple variables BMI and age. The paper shows an understanding of the effect of obesity on the quality and quantity of the limb movements and demonstrated the effectiveness of an arm band mounted n-core sensor in recording and categorising daily activity.

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