Can optimal marker weightings improve thoracohumeral kinematics accuracy?

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Abstract

Local and global optimisation algorithms have been developed to estimate joint kinematics to reducing soft movement artifact (STA). Such algorithms can include weightings to account for different STA occur at each marker. The objective was to quantify the benefit of optimal weighting and determine if optimal marker weightings can improve humerus kinematics accuracy. A pin with five reflective markers was inserted into the humerus of four subjects. Seven markers were put on the skin of the arm. Subjects performed 38 different tasks including arm elevation, rotation, daily-living tasks, and sport activities. In each movement, mean and peak errors in skin- *vs.* pins-orientation were reported. Then, optimal marker weightings were found to best match skin- and pin-based orientation. Without weighting, the error of the arm orientation ranged from 1.9° to 17.9°. With weighting, 100% of the trials were improved and the average error was halved. The mid-arm markers weights were close to 0 for three subjects. Weights of a subject applied to the others for a given movement, and weights of a movement applied to others for a given subject did not systematically increased accuracy of arm orientation. Without weighting, a redundant set of marker and least square algorithm improved accuracy to estimate arm orientation compared to data of the literature using electromagnetic sensor. Weightings were subject- and movement-specific, which reinforces that STA are subject- and movement-specific. However, markers on the deltoid insertion and on lateral and medial epicondyles may be preferred if a limited number of markers is used.

Keywords: Arm, Local optimization, Skin markers, Kinematics, Intracortical pins.

1 Introduction

Human movement kinematics is commonly assessed using stereophotogrammetry and skin-markers placed above bony landmarks. When skeleton kinematics is the subject of interest, the primary source of error in joint angles comes from the displacement of the skin-markers with respect to their underlying bones. This occurrence, termed as soft tissue artifact (STA), is the consequence of muscle contraction, skin elasticity, impacts, etc. (Peters et al., 2010). Efforts have been made to reduce errors due to STA, which are usually assessed using invasive methods: *e.g.* intracortical pins (Andersen et al., 2010; Reinschmidt et al., 1997b) or fluoroscopy (Stagni et al., 2005), for a review see Leardini et al. (2005). Such method have been used to investigate the lower-limb STA (Akbarshahi et al., 2010; Cappozzo et al., 1996; Reinschmidt et al., 1997b; Tsai et al., 2009), but few investigations focused on upper-limb (Hamming et al., 2012b; Matsui et al., 2006). Since STA are different between segments, *e.g.* thigh *vs* shank (Benoit et al., 2006; Camomilla et al.; Reinschmidt et al., 1997a; Stagni et al., 2005), further investigations are needed to identify suitable methods for reducing STA propagation to the upper-limb kinematics.

While marker sets exist for upper-limb use in conjunction with optoelectronics systems (Butler et al., 2010; Jackson et al., 2012), electromagnetic sensors are preferred in clinical studies for reasons of space and cost (Finley and Lee, 2003; Hamming et al., 2012a; Meskers et al., 1998; Stokdijk et al., 2003). Efforts have already been made to better track the scapula which slides under the skin (Lempereur et al., 2014). Regarding the humerus, errors up to 30° were reported in axial rotation due to STA (Hamming et al., 2012a) when using cuff mounted electromagnetic sensors. This error cannot be compensated for since one sensor on each segment does not provide any redundancy.

On the lower-limb, markers undergo different STA according to their location. On each marker, STA is composed of a rigid (or in-unison) component and a deformation (or own) component

(Andersen et al., 2012; Grimpampi et al., 2014; Leardini et al., 2005). Some authors have proposed mathematical models representing STA (Camomilla et al., 2013; Dumas et al., 2014) and others used least squares algorithms to reduce STA (Cheze et al., 1995), especially the deformation component, in so-called local optimization algorithms. To reduce the rigid component and avoid joint dislocation problems, chain models with set degrees of freedom in combination with nonlinear least squares algorithms (Begon et al., 2009; Laitenberger et al., 2014; Lu and O'Connor, 1999) or extended Kalman filters (Fohanno et al., 2014; Halvorsen et al., 2004) (termed as global optimization) have emerged.

Since STA is not uniform within and between the body segments, these algorithms were improved by introducing weightings, in both global (Alonso et al., 2007; Ausejo et al., 2011) and local optimization (Andriacchi et al., 1998). Each marker weight can manually be adjusted in the musculoskeletal OpenSim software (Delp et al., 2007). Lu and O'Connor (1999) introduced a weighting matrix to reflect the error distribution among the markers. For simplicity, they chose equal weightings for all the markers at the same segments but smaller weightings to the thigh than the pelvis and shank. Indeed skin movement artefact is bigger on the thigh (Cappozzo et al., 1996). In their application to the upper-limb, Roux et al. (2002) refined the weightings with segmental residual errors given by the algorithm of Söderkvist and Wedin (1994). Unfortunately, to the best of our knowledge, weighting values, methods for their identification, and assessment of the gain in accuracy have never been provided for lower-limb or upper-limb.

The objective of this study was to assess the effect of skin marker weightings in a local optimization algorithm on arm orientation accuracy. Firstly, optimal weightings for each skin

marker were obtained based on a gold standard humeral orientation. Then optimal weightings obtained for each movement and each subject were applied to other movements and other subjects to determine if weightings are subject- and/or movement-specific.

2 Method

2.1 Experiment

Four male subjects (age: 32, 41, 44 and 27 years, height: 1.72, 1.82, 1.77 and 1.65 m, mass: 80, 115, 82 and 57 kg, and BMI 27, 35, 26 and 21 $kg.m^{-2}$, for *S1* to *S4* respectively) volunteered after giving their informed consent. The protocol was approved by the ethic committees of both University of Montreal and Karolinska Institutet, where the experiment took place. As fully described in Dal Maso et al. (2014), an orthopaedic surgeon inserted a pin into the humerus under sterile surgery conditions. Five markers were secured on the pin (Fig. 1) to locate the humerus using an optoelectronic system (18 cameras, 2 and 4 Mpx at 300 Hz). The uncertainties of the segment position and orientation were estimated at 0.15 mm and 0.2°, respectively (Dal Maso et al., 2014). In addition, seven markers were put on the skin located as follows (Fig. 1B-C): (M_1) deltoid insertion, arm lateral (M_2) and medial (M_3) faces, on the middle arm over the triceps (M_4), under the insertion of the triceps tendon (M_5) and on the lateral (M_6) and medial (M_7) humeral epicondyles.

[Figure 1 about here.]

Each subject was instructed to hold a relaxed posture and to perform a series of (1) maximal arm elevations (elbow extended) with the arm in internal, neutral, and external rotation, as well as rotations (elbow flexed at 90°) at 30°, 60°, and 90° in ad-abduction and flexion-extension, (2) six daily living tasks, and (3) four sports activities. A total of 38 different movements were recorded. Ten trials were acquired during flexion, abduction, and rotation with the arm abducted at 0° and 90°, and during each daily-living task and sport activities. Only two trials for each movement were used for the subsequent analysis. Refer to the supplementary materials for an enumeration (Table 3) and illustrations (Fig. 5 and 6) of movements performed in series 1.

2.2 Initial arm misorientation

No signal processing (smoothing or filtering) was applied to the marker trajectories. The humerus orientation in the global reference frame (${}^{G}R_{h}$) was obtained from pin-markers using a segmental optimization algorithm (Roosen et al., 2013, AppendixB) and previous recommendations (Monnet et al., 2010). Based on skin-markers, the arm orientation (${}^{G}R_{a}$) was calculated using the said algorithm modified to include marker weightings as illustrated in Fig. 2. Initially the weightings were set to an equal value ($\omega_i = 0.378,\ i = 1, \dots, 7$ such that $\|w\| = 1$).

[Figure 2 about here.]

In the relaxed posture, the humeral and arm orientations based on pin- and skin-markers respectively were mathematically superimposed and the markers' geometry served as a reference (t_0 in Fig. 2) for the segmental optimization algorithm. During the movements, the misorientation

between ${}^{G}R_h$ and ${}^{G}R_a$ was calculated as the helical axis angle between skin and pin-based coordinates systems ${}^{h}R_a = \left({}^{G}R_h^{-1}\,{}^{G}R_a\right)$ (de Vries et al., 2010) as follows:

$$\theta = cos^{-1}\left(\frac{trace\left({}^{h}R_a\right)-1}{2}\right), \theta \in [0, \pi] \quad (1)$$

The angle-time histories ($\theta_0(t)$) associated to the helical axis were calculated and the mean and peak error were reported.

2.3 Optimal weightings

Weightings ($w = [\omega_1, \dots, \omega_7]$) applied to markers ($M_i$ for $i = 1, \dots, 7$) were optimized to minimize the error between the pin and skin-marker based matrices of rotation in the following constrained problem:

$$\min_{w} J(w) = \frac{1}{T}\sum_{t=0}^{T}\left\| {}^{G}R_h \; - \; {}^{G}R_a(w)\right\|_F$$

where at the frame t_1 $\quad \max_{R_a(w)^T R_a = I} tr\left[R_a \sum_{i=1}^{n}\left(\left(w_i p_i^{t_1}\right)\left(w_i p_i^{t_0}\right)^T\right)\right]$

subject to $\quad 0 \le \omega_i \le 1, \; i = 1, \dots, 7$

$$\|w\| = 1$$

For computational efficiency, the Frobenius norm of the difference between the two rotation matrices $\left(\left\| {}^{G}R_h \; - \; {}^{G}R_a(w)\right\|_F\right)$ was preferred to Eq. [1] in the fitness function. This problem with several local minima was solved using a hybrid optimization algorithm, which was run four times. The weightings associated to the fittest solution for each trial were retained. This two-step algorithm was composed of a genetic algorithm (150 individuals, elitist selection and 150

generations maximum) (Eiben et al., 1999) followed by a gradient-based algorithm to refine the solution. The algorithm parameters were adjusted to obtain consistent solutions, *i.e.*, at least twice the same fitness value over the four runs to ensure that global optimum was found. Finally, all the movements of each subject were also concatenated to determine overall optimal weightings.

2.4 Error reduction

After optimization, the angle-time histories (θ_{opt}, Eq. [1]) were calculated and the weighting effect on the orientation error was defined as the average change in θ:

$$\bar{E}_{trial} = \frac{1}{T}\sum_{t=0}^{T}\Big(\theta_{opt}(t) - \theta_0(t)\Big), \tag{3}$$

where a negative value indicates that the set globally reduces the error in arm orientation while a positive value means that the set fails to improve the accuracy. The dispersion of the sets of optimal weightings was measured using the coefficient of variation (CV). The average sets of the four subjects were qualitatively compared.

2.5 Are weightings subject-specific?

In a second step, each set of weightings optimized for one trial was applied to the other trial of the same movement and subject when movements were repeated, and to all trials of the same movement of other subjects. This permitted to determine if the weightings are subject-specific. For each set applied to each movement, Eq. [3] was used to quantify the error reduction or increase. The median value for all the movements of each subject gave a global score. Also the rate of improvement, defined as the ratio of the number of sets that improve the arm orientation and the total number of sets, was reported in percent.

2.6 Are weightings movement-specific and both movement- and subject-specific?

In a third step, each weighting set obtained for a subject was applied to all the trials of the same subject and to those of the three other subjects to determine if the weightings are movement- and subject-specific, respectively. Finally, the five sets that gave the greatest improvement in the overall trials of each subject were retained for the same analysis to determine the specificity of the best sets of one subject to the others. In each case, descriptive statistics were reported, namely, median, quartiles and percentage of trials with reduced error.

3 Results

3.1 Best scenario

Using seven skin-markers and no weighting, the orientation error ($\bar{\theta}_0$) ranged from 1.9° (*S4* arm abduction) to 17.9° (*S3*, combing). The participant with the smallest BMI, *S4*, showed an average error of 5.4±2.3° (with peak value of 11.1±4.5, see Table 1). The average error in *S1* was twice larger than in *S4*. The tasks subjected to the largest deviations were composed of large arm internal-external rotation (*i.e.*, all movements of internal-external rotations, comb hair and reach back). The smallest errors were found in elevations in adduction, flexion, abduction and extension.

[Table 1 about here.]

After optimizing the weightings, 100% of the trials were improved (Fig. 3A). The median error dropped of 4.7°, 2.6°, 2.9°, and 1.4 for the four subjects, respectively (Fig. 3A). The standard deviations of the weightings for each subject (Fig. 4A) were large, leading to CV up to 3.9 (1.45±0.82). Some weightings were close to 0 such as w_2 for *S1* and *S3*, w_3 for *S2*, w_4 for *S3* and

w_5 for *S2* and *S3* (Fig. 4A). In other words, these markers were quasi excluded from the orientation calculation.

[Figure 3 about here.]

[Figure 4 about here.]

3.2 Weightings applied to trials of the same movement

As illustrated in (Fig. 3B), only 3 conditions out of 12 revealed an overall improvement when the weightings obtained for a subject and a movement were applied to three others subjects and the same movement. The rate of improvement ranged from 15% (optimal weightings of *S1* applied to the same movements of S2) to 82% (optimal weightings of *S4* applied to the same movement of *S3*).

3.3 All weightings applied to each trial

When each set of weightings was applied to each trial of the same subject, the accuracy was not systematically increased (Fig. 3C). The rate of improvement dropped to 68%, 87%, 68%, and only 44%, for *S1* to *S4*, respectively. The median overall improvement was lower than 1.7° and an increased error was noticed in *S4* (+0.2°). When considering the effect on the trials of the other subjects, the rate of improvement ranged from 14% (all optimal weightings of *S1* applied to each trial of *S4*) to 65% (all optimal weightings of *S4* applied to each trial of *S3*).

In all cases, weightings of a subject applied to himself gave a better rate of improvement and decreased error than weightings optimized for another subject (Fig. 3C). Noteworthy, the

weighting sets of *S4* decreased the median error by 0.5° with a rate of improvement of 65% when applied to *S3* (versus 1.1 and 68% for weightings of *S3* applied to *S3*).

3.4 Selected sets

Only in *S3*, the set obtained from all of the movements grouped together ("ALL" in Table 2) gave the best result. This set was also found within the best sets for *S1* and *S3* but not *S4*. The arm internal-external rotation with 90° of abduction was found within the best sets for three subjects. Within these sets for each participant, most belonged to the first series of movements. The exceptions were "reach pocket"' (*S1*) and "hockey shooting" (*S2*). Qualitatively, the dispersion of the weightings (Fig. 4B) for the five selected sets was similar to the dispersion of all the trials (Fig. 4A): 0.19<CV<2.17.

When these five selected weighting sets obtained for a subject were applied to each trial of the same subject, the results were improved. The rate of improvement ranged from 77% (*S3*) to 99% (*S1*) and the median error decreased from 0.5° (*S4*) to 2.4° (*S1*) (Fig. 3D). When these five selected weighting sets were applied to another subject, the median error was increased in all cases, except for weightings of *S3* applied to *S1* and *S4* applied to *S3* (Fig. 3D). In *S4*, the rate of improvement was higher than when its own selected weightings were applied to himself (93% *vs.* 87%), but the median improvement remained smaller (1.1° *vs.* 2.1°) (Fig. 3D).

[Table 2 about here.]

4 Discussion

The present study assessed the effect of skin marker weightings in local optimization on the accuracy of arm orientation. In line with the early works of Lundberg (1996), using qualitative validation, we explored a method to reduce STA. Based on a gold standard measure (i.e.,

intracortical pin with five markers reconstructed using 18 cameras), our main findings are that (*i*) the expected improvement varies between 1° and 5° in the best but unrealistic scenario; (*ii*) weightings are movement- and, above all, subject-specific; (*iii*) generic weightings were unfortunately not found.

Similar to most of the experiments based on gold standard kinematic methods (intracortical pins (Benoit et al., 2006; Reinschmidt et al., 1997b) or fluoroscopy (Akbarshahi et al., 2010)), the present study included a small number of participants due to the invasiveness of the protocol. The exception is certainly the large investigation about the shoulder complex led by P. Ludewig (Hamming et al., 2012a; Ludewig et al., 2009) with both asymptomatic participants and patients with shoulder impingement using electromagnetic sensors. Nevertheless the present results are the first to examine the interest of weightings in least-squares algorithms to reduce STA, that can be easily implemented in Levenberg-Marquardt or Newton-Gauss algorithms when estimating joint angles by inverse kinematics.

Furthermore most studies with gold standard data were restricted to a few movements, namely walking, cutting and running, and above all to the lower-limb (Benoit et al., 2006; Reinschmidt et al., 1997b). For the upper-limb, the studies were restricted to the scapula during static poses (Matsuki et al., 2012), *ex-vivo* passive movements (Cereatti et al., 2015), and arm flexion, scaption and abduction and rotations with the arm abducted at 0° and 90° (Hamming et al., 2012a; Ludewig et al., 2009). Our protocol deeply assessed marker weighting process for a total of 38 dynamic movements including above-mentioned standardized elevations and rotations but also daily-living

and sports activities. Our study may significantly contribute to benchmark data for testing new algorithm for STA attenuation.

4.1 Initial error and maximal improvement

A redundant marker set (n=7) provided an accurate estimate of the humerus orientation without signal processing or weightings. With seven skin-markers, the maximal error (20.1±3.4° and 16.5±1.8° during arm internal-external rotation with the elbow abducted at 0° and at 90°) was about 30% lower than when a single electromagnetic sensor was fixed on a cuff (Hamming et al., 2012a). In the latter and present studies, greater errors were found close to maximum internal and external rotation and in subjects with BMI greater than 25. Markers redundancy in least squares algorithms is effective to reduce skin movement artefact as recommended by previous (Challis, 1995; Monnet et al., 2010). Motion analysis systems are now able to track several markers with limited human assistance. Though electromagnetic sensors are commonly used in upper-limb clinical studies, markers redundancy would be of interest as already suggested by Roux et al. (2002) especially during large range of humerus axial rotation. Moreover, our results were obtained using seven skin-markers while generic models require usually about three markers per segment. It is expected that the performance of weighted algorithms would be affected by the redundancy. Further analyses could lead to more convincing results of optimal weightings with a usual set of about three markers.

With optimal marker weightings the error dropped to less than 5°, resulting in an average error of about 5°. Optimal weightings may double the accuracy of the arm orientation measurement. However this improvement is theoretical since it is impossible to determine *apriori* these weightings which have been show to be subject- and movement-specific. Indeed, skin-markers are not only affected by random skin movement artefact with normal distribution, which would be

fully compensated for in a least-squares algorithm. In addition to their own component, markers undergo a in-unison component (Andersen et al., 2012) that explains the residual error relative to the bone kinematics. This component could be minimized using global instead of local optimization. When segments are linked to each other with defined (n<6) degrees of freedom in a kinematical chain (Lu and O'Connor, 1999), there are compensations between degrees-of-freedom to ensure physiological movements, *i.e.*, without apparent joint dislocations. This advantage remains to be addressed since the choice of the joint type *e.g.*, hinge, parallel mechanism, ball and socket as well as the segment length become another source of error (Duprey et al., 2010), which could lead to an increased joint kinematics error (Andersen et al., 2010). Double calibrations are efficient for quasi-planar movements in both lower (Stagni et al., 2009) and upper limb (Cereatti et al., 2015), but has never been tested on daily living and sports activities. The latter are three-dimensional and may require multiple calibrations and a more complex correction model.

4.2 Weightings are movement- and subject-specific

One out of the four subjects (*S4* on the diagonal of Fig. 3C) had a rate of improvement lower than 50%, when weightings found for each task were applied to the other tasks of the same subject. In this case, all markers may be weighted equally. Regarding inter-subject effect, in 9 out of 12 cases (Fig. 3B, except the diagonal) the rate of improvement is lower than 50% when weightings of one movement and one subject were applied to the same task in other subjects. This ratio jumped to 11 out of 12 cases (Fig. 3C) when other tasks were considered, resulting in subject and task combined effect. The large variety of movements assessed in this study produced high CVs, which highlights that weightings and beforehand STA are movement specific. The present results generalize to the humerus the finding of (Reinschmidt et al., 1997a; Reinschmidt et al., 1997b) and Benoit et al. (2006) that showed that markers displacements as well as their effects on joint or bone

kinematics are subject- and movement-specific. While the sample of participants is small in study investigating STA using intracortical pin, they all converged toward this conclusion whatever the age of the subjects (Benoit et al., 2006; Stagni et al., 2005).

However, the subject-specific weightings (Fig. 4) tended to show that some markers were quasi-excluded ($\omega_i < 0.01$). Except for *S2*, markers placed on the mid-arm ($M_{2,3,4}$) (Fig. 1) had the lowest weightings. Markers located on the deltoid insertion as well as lateral and medial epicondyles $M_{1,6,7}$ may be preferred for a set using a limited number of markers. However, the inter-subject differences and the small sample cannot lead to recommendation about optimal marker sets on the arm but could orient the marker set of future study. Finally, further analysis should focus on the characterization of the rigid component based on marker cluster geometrical transformations (Dumas et al., 2014) to better characterize the propagation of the rigid STA component. In this perspective, our study has contributed to a benchmarking database.

5 Conclusion

By comparison to an intracortical pin experiment, the average error of a skin marker based method to estimate humerus orientation was about 10° and could be reduced to 5° when applying optimal marker weightings in a least-square algorithm. Unfortunately, there is no generic set of weightings that will systematically improve the accuracy for all kinds of movements and subjects. While non-invasive techniques to personalize weighting do not exist, using a redundant marker set without weightings should be favored.

6 Conflict of interest statement

The authors have no conflict of interest to declare.

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7 Figures and Tables legends

Figure 1: Five markers are secured on a pin screwed in the humerus and seven markers (*Mi*) placed on the arm skin.

Figure 2: Representation of the local optimization algorithm without and with marker weightings. In each time-frame *t*, the matrix of rotation is optimized to best fit vectors p_i defined between the markers' centroid $\bar{M}$ and markers M_i with respect to a reference frame t_0 where skin movement artefact is assumed to be 0.

Figure 3: Change in misorientation (in degrees) for the trials of the four subjects (in rows) according to weighting sets of all four subjects (in columns) when (A) weightings were optimized trial by trial (best scenario); (B) weightings optimized for a movement were applied to the other trials of the same movement; (C) all weightings were applied to each trial; and (D) five best weightings were applied to each trial. *Note*. In this matrix representation, diagonal subplots represent weightings of a subject applied to the same subject; other subplots represent weighting of a subject applied to the other subjects. Negative values correspond to an overall improvement. The median value and the percentage of trials with a reduced error are displayed for each box. On each box, the central mark is the median, the edges of the box are the 25^{th} and 75^{th} percentiles, the whiskers extend to the most extreme data points without considering outliers (beyond ±2.7 standard deviations).

Figure 4: Optimal weightings for the four subjects, (A) means and standard deviations of all the movements, and (B) only the five movements that gave the best overall improvement for each subject. The horizontal line at 0.378 corresponds to the reference value, such that $\|w\| = 1$.

Table 1: Misorientation (Eq. [1] mean ± SD in degrees) before and after optimization for the average and peak θ values

Table 2: Five movements of each subject that gave the smallest median values across all the trials of the subject. Trial "ALL" corresponds to the concatenation of all the trials