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Optimising filtering parameters for a 3D motion analysis system

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ABSTRACT

In the analysis of movement data it is common practice to use a low-pass filter in order to reduce measurement noise. However, the choice of a cut-off frequency is typically rather arbitrary. The aim of the present study was to evaluate a new method to find the optimal cut-off frequency for filtering kinematic data. In particular, we propose to use rigid marker clusters to determine the dynamic precision of a given 3D motion analysis system, and to use this precision as criterion to find the optimal cut-off frequency for filtering the data. We tested this method using a model-based approach in a situation in which measurement noise is a serious concern, namely the registration of the kinematics of swimming using a video-based motion analysis system. For the model data we found that filtering the data with a single cutoff frequency of 6 Hz under some conditions decreased the accuracy of the reconstruction of the kinematics compared to using the unfiltered data. If the cut-off frequency was used that yielded optimal dynamic precision, then the accuracy improved by 29% compared to using raw data irrespective of the cluster position, close to the optimal accuracy improvement of 30%. We confirmed in an experiment that the cut-off frequency at which optimal precision was found varied between cluster positions and subjects, similar to the results obtained with the model. We conclude that 3D motion analysis systems can be made more accurate by optimising the cut-off frequency used in filtering the data with regard to their precision. Furthermore, the dynamic precision method seems useful to evaluate the effect of various filtering procedures.

1. Introduction

Motion analysis is widely used to study human motor behaviour. As measurement noise is inevitable, it is common practice to low-pass filter the kinematic data in order to reduce the effects of measurement noise. If the relevant frequency content of the raw signal is known, then numerous methods are available to distil the relevant signal. However, in movement analysis it is often unknown which part of the frequency content represents the actual movement. In that case, the experimenter has to choose an appropriate filtering procedure, and decide what cut-off frequency should be chosen in this procedure. Using a high cut-off frequency removes only very little noise, whereas a low cut-off frequency will introduce artefacts in the trajectory.

Bartlett (2007) stated that cut-off frequencies between 4 and 8 Hz are often used in filtering movement data. In most studies, the arguments for choosing a particular smoothing procedure and cut-off frequency are not specified, even though several quantitative measures have been proposed to objectively determine the optimal filtering procedure (Corradini et al., 1993; Cappello et al., 1996). These measures are based on the difference between the filtered and raw data. An alternative for optimising filtering in case the relevant frequency spectrum is unknown, which has not been recognised and investigated before, is to use the resulting precision of the 3D motion analysis system in question as a criterion for finding the optimal filtering frequency. We investigated the merits of this new *dynamic precision method* in the kinematic analysis of underwater swimming, where high-precision motion analysis systems with active markers based on infrared technology, such as Optotrak®, cannot be used due to the aquatic environment and passive, video-based systems have to be used instead. Moreover, experimental set-ups for underwater 3D reconstruction using video cameras (e.g. Ceccon et al., 2013; Silvatti et al., 2013) were found to be less precise compared to values obtained above water (Ehara et al., 1995). Therefore, underwater environments represent a context where optimising precision is of particular concern.

The precision of motion analysis systems is usually assessed under either static or dynamic conditions. In static conditions, the average deviation in the reconstruction of non-moving marker

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coordinates from the known positions is taken as a measure of accuracy. In dynamic conditions, precision is determined by calculating the variation in distance between two or more markers fixed on a rigid body moving through the calibrated volume (Haggard and Wing, 1990). Since movement analysis systems are used to reconstruct movements, the precision in dynamic conditions is more important than in static conditions. Ideally, precision should be determined during the registration of the movement of interest itself (e.g. swimming). As far as we know, however, no study to date has determined the precision of a motion analysis system in this manner. Here, we will test whether this dynamic precision method yields a filter frequency that corresponds to the one that optimises filtering. This can be done using any set of filters; in the present study we will use it to determine the optimal filter frequency of a Butterworth filter.

Quantifying underwater motion is important in the study of swimming because, as in many other sports, technique is considered one of the most important factors for achieving a good performance. Technique has been studied mostly by determining temporal and spatial characteristics of the stroke (e.g. Suito et al., 2008; Rouard, 2011). Some authors have examined arm trajectories in relation to the generation of propulsive force (e.g. Schleihauf, 1979; Berger et al., 1995) and performance level (e.g. Deschodt, 1996). However, as pointed out by Ceccon et al. (2013), the majority of kinematic studies do not provide a full description of joint kinematics in terms of Euler angles. This might be related to the poor visibility of bony landmarks during the stroke and the complex calculations that are needed to convert kinematic data to Euler angles. To determine segment orientations, additional technical markers on the skin of the subject may be used, a method called the Calibrated Anatomical System Technique (CAST) (Cappozzo et al., 2005). Recently, Ceccon et al. (2013) were the first to employ this technique in swimming research. They concluded that the use of additional technical markers led to an increase in the percentage of video frames in which segment positions and orientations could be determined.

In the present study, technical markers were not only used for good visibility in the video captures, but also to determine the dynamic precision of the movement registration used by placing the technical markers as rigid body clusters on the segments. In particular, we employed actual swimming data and simulations with added measurement noise to determine the dynamic precision of a bout of movement registration, and subsequently used this precision to optimise filter frequency. For each rigid body (with several markers attached to it), we determined how dynamic precision depended on the filter frequency, and determined the frequency (f_{dp}) that yields optimal dynamic precision of the resulting movement registration. We obtained similar results for both model and experimental data. We used the model simulation to check that f_{dp} corresponded to the cut-off frequency that optimised the accuracy.

2. Methods

2.1. Model

We used a model of the swimming movement (corrupted by measurement noise) to establish to what extent the filter frequency at which optimal dynamic precision was achieved improved accuracy (i.e. improved reconstruction of the uncorrupted trajectory). The model of Payton et al. (1997) incorporates the movement of the trunk and arm to simulate the front crawl movement in swimming. It was used to study swimming kinematics and is therefore suitable to address the current research question. The model (see Fig. 1) consists of the following segments: trunk (half width: Q to S), upper arm (S to E) and forearm/hand (E to H). By supplying the angle-time profiles for the body roll angle (θ), shoulder abduction angle (α), elbow flexion angle (β) and shoulder extension angle (ϕ), in combination with the trunk midpoint position Q, the kinematic data of the swimming movement can be generated.

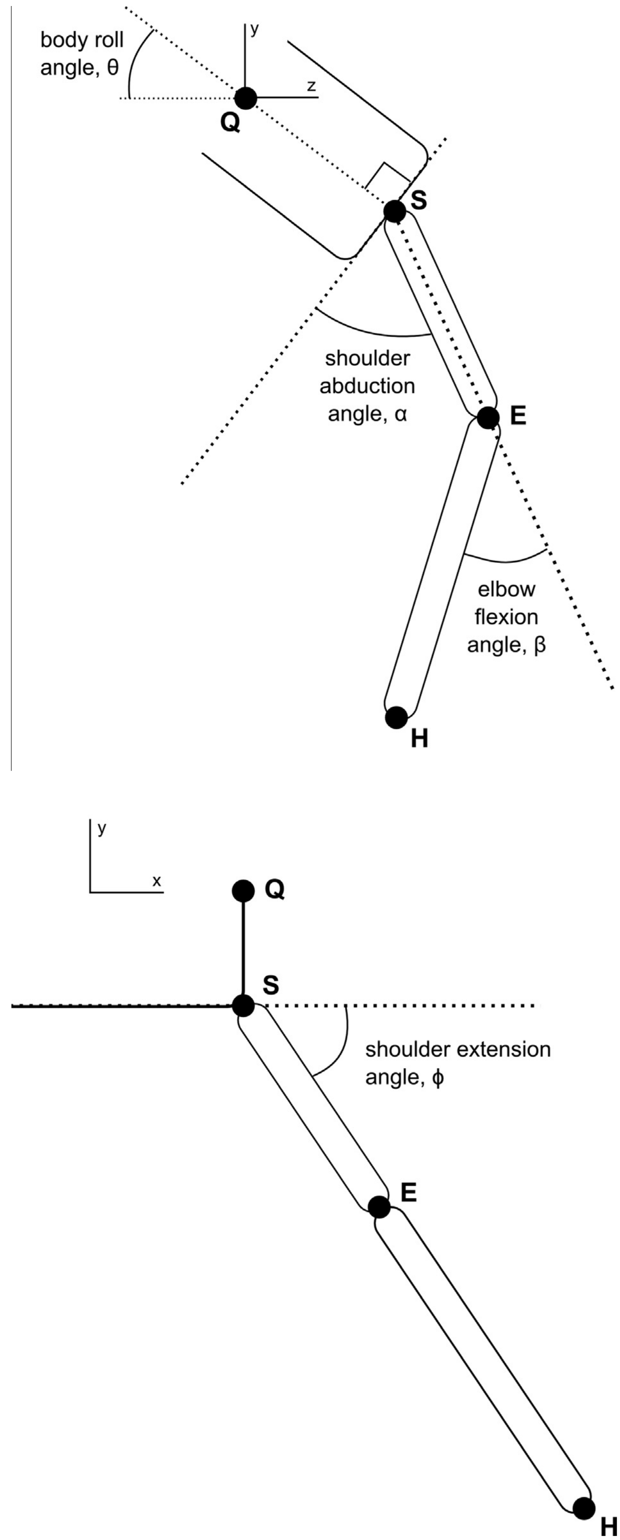

Fig. 1. Kinematic model viewed from behind (top) and from the side (bottom).

The angle time profiles as described in the methods section of Payton et al. (1997) were converted to the following five equations:

$$\theta(t) = \theta_{\max}\sin\left(\pi\frac{t}{t_{\text{pull}}}\right) \tag{1}$$

$$\alpha(t) = \frac{1}{2}\alpha_{\max}\left(1-\cos\left(2\pi\frac{t}{t_{\text{pull}}}\right)\right) \tag{2}$$

$$\beta(t) = \frac{1}{2}\beta_{\max}\left(1-\cos\left(2\pi\frac{t}{t_{\text{pull}}}\right)\right) \tag{3}$$

$$\phi(t) = 180\frac{t}{t_{\text{pull}}} \tag{4}$$

$$Q_x(t) = v_{\text{swim}}t \tag{5}$$

The maximum body roll ($\theta_{\max}$), shoulder abduction ($\alpha_{\max}$) and elbow flexion ($\beta_{\max}$) angles were set at 45°, 90° and 60°, respectively. The swim speed (v_{swim}) was fixed at 1.6 m s^{-1}. The lengths of the trunk (Q to S), upper arm and forearm/hand segments were modeled to be 0.25 m, 0.35 m and 0.50 m, respectively. Three marker clusters consisting of three markers each (see Fig. 2) were added to the model at the most distal position on the upper arm and forearm/hand segment and at the most cranial position on the trunk. Raw real world marker data were obtained by adding Gaussian noise (σ = 1.4 mm) to the x, y and z marker coordinates generated by the model. In this manner, the model generated a dataset of 100 swimming trials with a long pull duration time (t_{pull} = 0.75 s) and 100 swimming trials with a short pull duration time (t_{pull} = 0.60 s).

Subsequently, the real world marker data were filtered with a zero lag, second order low pass Butterworth filter. This filtering removed some of the added measurement noise, but also introduced artefacts. By using various cut-off frequencies ranging between 2 and 14 Hz (the same for all markers of a cluster) we could establish the effect of filtering on the accuracy (difference between filtered signal and original signal without noise). The accuracy was compared between values obtained with raw data, using a cut-off frequency of 6 Hz, the cut-off frequency (f_{dp}) at which dynamic precision was optimal, and the cut-off frequency (f_{opt}) for which accuracy was optimal. The cut-off frequency of 6 Hz was chosen for comparison, since it was previously used (e.g. Cappaert et al., 1995; Gourgoulis et al., 2008) in filtering underwater kinematic front crawl data.

The dynamic precision σ_{dist} was based on the standard deviation of the distances between marker points AB, BC and AC and calculated as follows for each of the rigid bodies:

$$\sigma_{\text{dist}} = \text{mean}(\sigma_{\text{AfBr}}, \sigma_{\text{ArBf}}, \sigma_{\text{BfCr}}, \sigma_{\text{BrCf}}, \sigma_{\text{AfCr}}, \sigma_{\text{ArCf}}) \tag{6}$$

where σ_{AfBr} represents the standard deviation of the distance between marker points A and B, based on the filtered position data of marker A (subscript f) and the raw position data of marker B (subscript r). σ_{ArBf} represents the standard deviation of the distance between markers A and B, based on the raw position data of marker A and the filtered position data of marker B, and so on.

As a measure for the accuracy of the data processing, we used the root mean squared difference (RMSD) between the (un)filtered data and the modeled data (without noise) for the three markers:

$$\text{RMSD} = \sqrt{\frac{1}{N}\sum_{n=1}^{N}\sum_{i=1}^{3}\left(\left(A_{n,i}^{\text{proc}} - A_{n,i}^{\text{model}}\right)^2 + \left(B_{n,i}^{\text{proc}} - B_{n,i}^{\text{model}}\right)^2 + \left(C_{n,i}^{\text{proc}} - C_{n,i}^{\text{model}}\right)^2\right)} \tag{7}$$

where the superscript *model* refers to the modeled kinematic data (without noise) and the superscript *proc* refers to the data after addition of measurement noise (raw or filtered). The subscript i refers to the data from the x (i = 1), y (i = 2) and z (i = 3) axis, respectively. N represents the number of kinematic data points.

For each trial the RMSD was determined when no filtering was applied ($\text{RMSD}_{\text{nofilt}}$), at a cut-off frequency of 6 Hz (RMSD_{6Hz}), at the cut-off frequency at which the optimal value for dynamic precision was found (RMSD_{dp}), and at the cut-off frequency at which the optimal value for accuracy was found (RMSD_{opt}), in order to establish the effect of different cut-off frequencies on the accuracy of the resulting data.

2.2. Experiment

To determine whether the characteristics of f_{dp} as determined by using the model corresponds to that during actual swimming, measurements of the front crawl movement were obtained from five swimmers. The experimental protocol was approved by the ethical committee of the Máxima Medical Centre (Eindhoven). The subjects (see Table 1) signed an informed consent form prior to participation. Sets of three LEDs clustered on a rigid body (see Fig. 2) were placed on three positions on the body: the chest, the

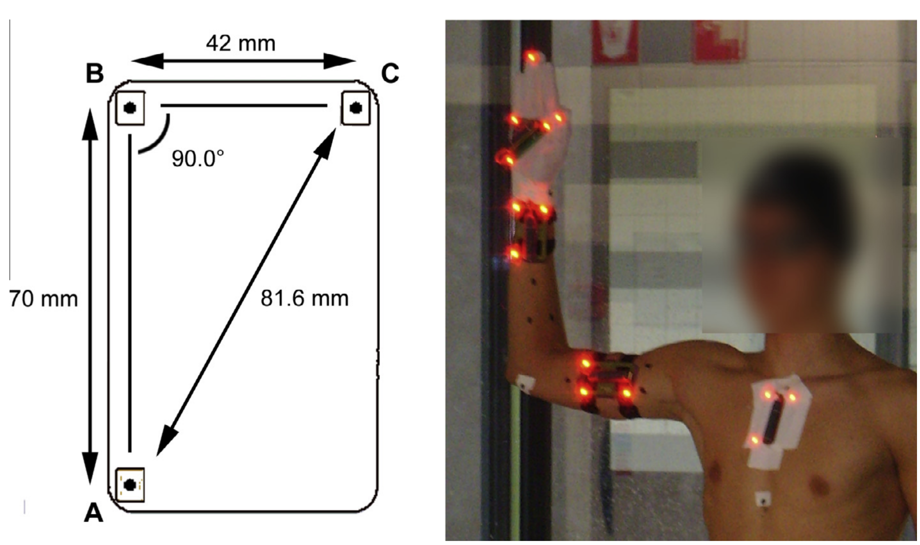

Fig. 2. The rigid body with three LEDS (A–C) mounted on it.

Table 1
General information about the subjects.

Subject	Gender	Body height (cm)	Body mass (kg)	Years of competition experience
1	F	164.5	53	7
2	F	170.0	61	6
3	M	183.0	72	10
4	F	171.0	52	5
5	M	175.5	59.5	5

right upper arm and the right forearm. LEDs were used to have clearly visible markers; none of the swimmers did complain about the rigid bodies affecting their swimming. After a 15 min warm up, swimmers performed a 200 m front crawl race in a 50 m pool starting and finishing the race with a turn. They were instructed to complete the 200 m distance in the shortest possible time, without any instruction about race strategy.

Two cameras (Basler, scA1400-gc, 30 fps), fixed in the wall at 35 m and 45 m from the start of the pool, were used to determine the average swimming velocity and stroke frequency in this part of the pool during the first lane of the race. Furthermore, six cameras (Basler, 30 fps) were placed (see Fig. 3) in an underwater housing at the bottom of the pool (2.20 m depth) to record the swimming movement at the end of the first lane. The data from these cameras were combined using Direct Linear Transformation (DLT) algorithm and employed for motion analysis of the swimming stroke. A pulse generator (National Instruments, Texas, USA) was used to trigger the cameras and synchronization of the six cameras was accomplished by activating a LED positioned next to the calibrated volume, which was visible in the video captures.

Prior to the measurements, the intrinsic camera calibration parameters were determined from underwater camera captures of a checkerboard using the 'Camera Calibration Toolbox' (Bouguet, 2008) in Matlab (The Mathworks). The intrinsic parameters were used to correct image coordinates for radial and tangential distortions. Subsequently, 23 control points on a $2 \times 1 \times 1$ m calibration frame were used to determine the 11 DLT constants per camera (Abdel-Aziz and Karara, 1971).

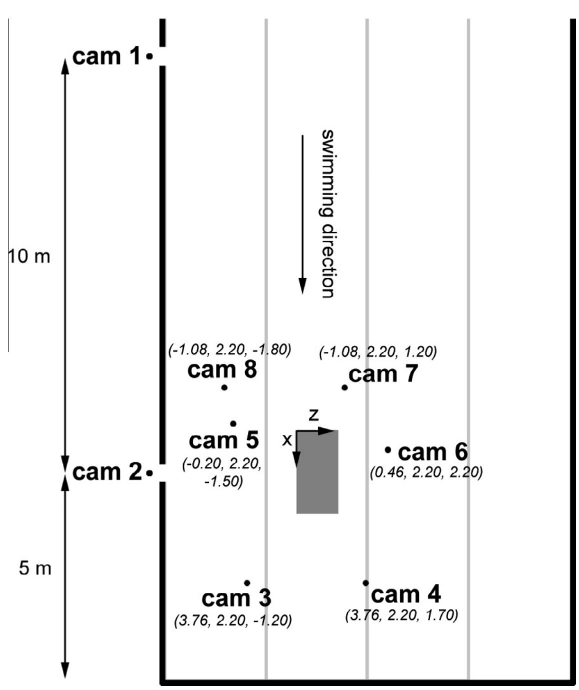

Fig. 3. Positioning of the two cameras (cam 1 and 2) in the wall and the six cameras (cam 3–8) used for 3D reconstruction around the calibration volume (grey square). Camera coordinates are given in meters relative to the upper left corner of the calibration volume.

We collected data during the underwater part of a single arm stroke. The 3D kinematic data were determined by manually identifying the markers in each frame (by a skilled operator using a custom-made Matlab script). After identification of the image coordinates, the 3D coordinates for each of the markers were calculated based on the DLT method. In frames where the 3D coordinates could not be calculated due to lack of visibility of the markers in the video footage, the missing values were linearly interpolated if data were not missing in more than three subsequent frames. Calculated coordinate data were also replaced by linearly interpolated data points in frames where the reconstructed distance between two marker points on the rigid body deviated more than 4 standard deviations from the mean reconstructed distance. Subsequently, the 3D coordinates of each marker were filtered with a second order low pass Butterworth filter. The effect of filtering on precision was established by using various cut-off frequencies between 2 and 14 Hz (the same for all markers of a cluster) to determine whether differences were present in f_{dp} between subjects and cluster positions.

2.3. Statistical analyses

Statistical analyses were performed on the results of the model simulations. A repeated measures ANOVA was used to determine the effect of cut-off frequency (no filtering, 6 Hz, f_{dp} and f_{opt}) on the accuracy of the kinematic data (RMSD). Furthermore, a 3×2 mixed ANOVA was used to determine the difference in f_{dp} and f_{opt} between both cluster positions (chest, upper arm and forearm) and between both pull times (short and long). Mauchley's test of sphericity was used to correct the degrees of freedom of the ANOVA. The Huynh–Feldt correction was used if the Greenhouse–Geisser epsilon was greater than 0.75. Otherwise, the Greenhouse–Geisser correction was used. If a significant main effect was found, post hoc analysis was performed using Bonferroni corrected pair-wise *t*-tests. Partial eta squared was calculated as a measure of effect size.

3. Results

3.1. Model

The effects of cut-off frequency on dynamic precision are shown for a characteristic trial of the simulated data in Fig. 4. As can be seen, dynamic precision is not only dependent on cut-off frequency, but also on cluster position. As expected, the curves all show a minimum, corresponding to the optimal dynamic precision. The frequency f_{dp} for which this optimum was obtained differed between the three cluster positions.

The accuracy values resulting from the different filtering procedures applied to the kinematic data from the model are shown in Fig. 5. Filtering with 6 Hz (light grey bars) reduced the accuracy relative to the raw data (white bars) for some cluster/pull time combinations. The accuracy as obtained using the filter frequency given by the dynamic precision method (dark grey bars) was very close to the optimal accuracy (black bars).

In the long pull time condition there was a significant main effect for the different filtering procedures on the accuracy of the marker clusters at the chest ($F(1.7,170.3) = 5650.6$, $p < .001$, $\eta_p^2 = .98$), upper arm ($F(1.7,164.5) = 2516.0$, $p < .001$, $\eta_p^2 = .96$) and forearm ($F(1.7,172.6) = 2897.5$, $p < .001$, $\eta_p^2 = .97$). For all marker clusters, post hoc analysis revealed significant differences in accuracy between all filtering procedures ($p < .05$). Filtering the

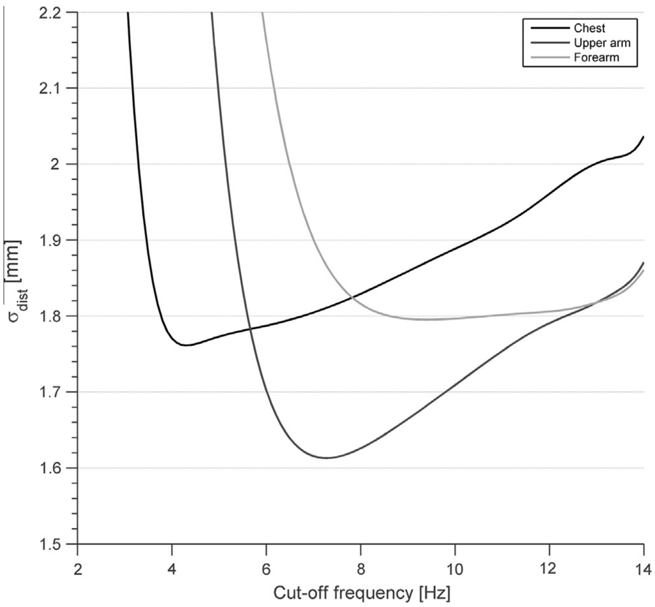

Fig. 4. The relationship between cut-off frequency and the dynamic precision (σ_{dist}) in a single trial (long pull time) of the model data.

simulated chest data with a 6 Hz cut-off frequency improved the accuracy by 37 ± 4% compared to the accuracy of the unfiltered data. The dynamic precision method improved accuracy by 43 ± 5% relative to the unfiltered values, which is close to the maximal possible improvement (44 ± 4%) using the optimal filter frequency. For the upper arm we found that filtering with cut-off frequency of 6 Hz improved the accuracy by 17 ± 5% in comparison with the accuracy of the unfiltered data. Filtering with f_{dp} and f_{opt} improved accuracy by respectively 27 ± 4% and 28 ± 4% relative to the unfiltered values. Filtering with 6 Hz reduced accuracy by 4 ± 6% with respect to the accuracy of the unfiltered data for the forearm kinematic data. In contrast, filtering using the cut-off frequencies f_{dp} and f_{opt} improved the accuracy relative to the unfiltered data by respectively 22 ± 3% and 23 ± 3% for the forearm marker cluster.

Also in the short pull time condition we found a significant main effect of the filtering procedure on the accuracy of the marker cluster at the chest ($F(1.5,146.2) = 4346.0$, $p < .001$, $\eta_p^2 = .98$), upper arm ($F(1.7,168.6) = 5748.3$, $p < .001$, $\eta_p^2 = .98$) and forearm ($F(1.4,136.1) = 9505.5$, $p < .001$, $\eta_p^2 = .99$). Post hoc analysis revealed significant differences in accuracy between all filtering procedures for each marker location ($p < .05$). Filtering the kinematic data from the chest marker cluster with a cut-off frequency of 6 Hz led to a 36 ± 4% better accuracy compared to the accuracy of the unfiltered data. Filtering at cut-off frequency f_{dp} improved accuracy by 41 ± 5% relative to the unfiltered values. The maximal improvement through filtering was 42 ± 5% by using f_{opt} as filter frequency. For the upper arm kinematic data, filtering with a cut-off frequency of 6 Hz deteriorated the accuracy by 32 ± 8% relative to the accuracy of the unfiltered kinematic data. Filtering the kinematic data with cut-off frequencies f_{dp} and f_{opt} improved accuracy by respectively 21 ± 4% and 22 ± 3% with respect to the accuracy of the unfiltered data. Filtering with a cut-off frequency of 6 Hz also reduced accuracy by 57 ± 10% with respect to the accuracy of the unfiltered data for the kinematic data of the forearm marker cluster. When the data were filtered using the cut-off frequencies f_{dp} and f_{opt} the accuracy relative to the unfiltered data improved by 18 ± 3% for both frequencies.

The cut-off frequencies that resulted in optimal dynamic precision and optimal accuracy are shown in Fig. 6. We found a significant main effect for cluster position on f_{dp} ($F(2.0,390.3) = 3567.7$, $p < .001$, $\eta_p^2 = .95$) and f_{opt} ($F(2.0,386.5) = 15482.8$, $p < .001$, $\eta_p^2 = .99$). The post hoc analysis showed significantly different values for f_{dp} and f_{opt} between the marker cluster placed on the chest, upper arm and forearm. We also found a significant main effect for pull duration on both f_{dp} ($F(1,198) = 268.6$, $p < .001$, $\eta_p^2 = .58$) and f_{opt} ($F(1,198) = 958.9$, $p < .001$, $\eta_p^2 = .83$). Overall, the post hoc

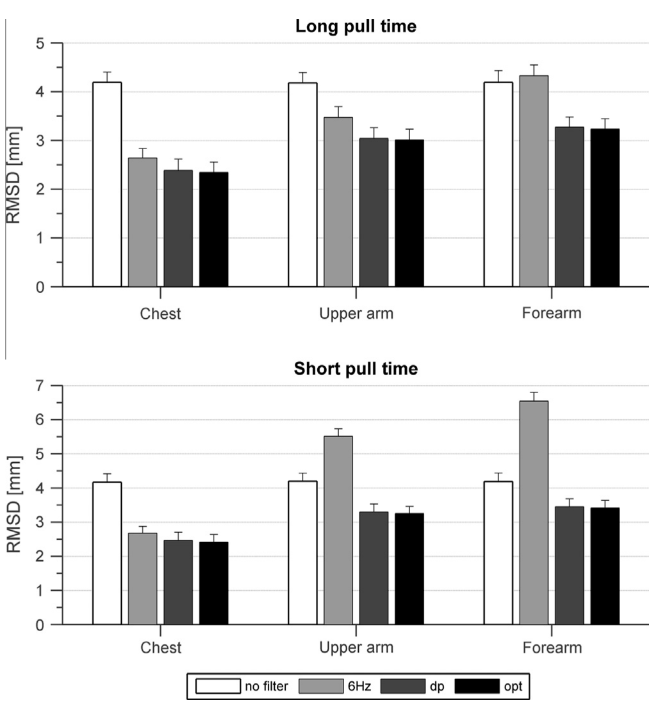

Fig. 5. Mean (±inter-trial standard deviation) accuracy values using the different filtering procedures.

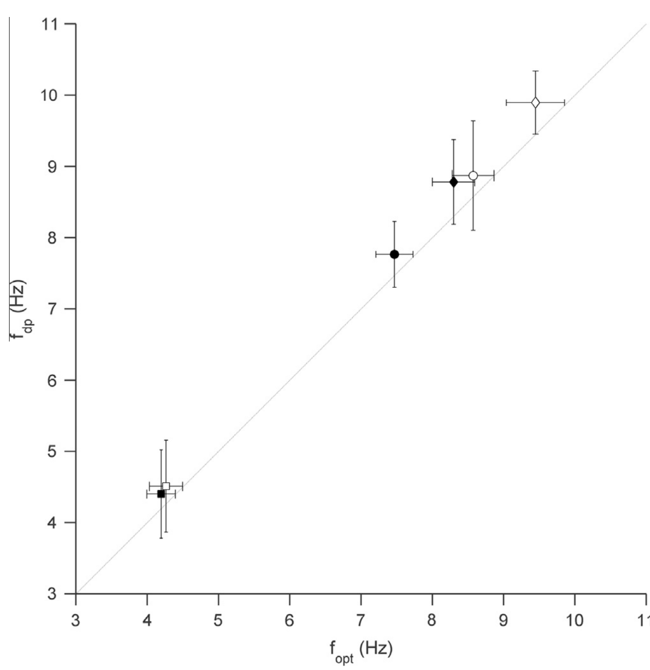

Fig. 6. Mean (±inter-trial standard deviation) cut-off frequencies at which optimal dynamic precision (f_{dp}, in Hz) and optimal accuracy (f_{opt}, in Hz) were obtained with the model data for the chest (square), upper arm (circle) and forearm (diamond) marker cluster in the long (closed symbols) and short (open symbols) pull time.

analysis revealed significantly higher values for f_{dp} and f_{opt} in the short pull time condition compared to the long pull time condition. Also a significant interaction effect was found between cluster position and pull time for f_{dp} and f_{opt}. The post hoc analysis revealed that the value of f_{dp} for the chest marker cluster was not significantly different between the short and the long condition ($F(1,198) = 1.48$, $p = .226$). For the upper arm ($F(1,198) = 151.69$, $p < .001$) and forearm marker cluster ($F(1,198) = 225.57$, $p < .001$) a significant difference in f_{dp} was found. For f_{opt}, significant differences between the short and long condition were found for the marker clusters at the chest ($F(1,198) = 5.08$, $p = .025$), the upper arm ($F(1,198) = 792.42$, $p < .001$) and the forearm ($F(1,198) = 516.83$, $p < .001$).

3.2. Experiment

The results with respect to the effect of different cut-off frequencies on dynamic precision (σ_{dist}) during actual swimming are shown for an exemplary subject in Fig. 7. The curves in this figure are comparable to those in Fig. 4: also for actual swimming data there is a minimum in the dynamic precision, and the relationship between cut-off frequency and precision is dependent on cluster position and subject. Therefore, the cut-off frequency at which the dynamic precision is optimal varies between cluster positions and subjects (see Table 2).

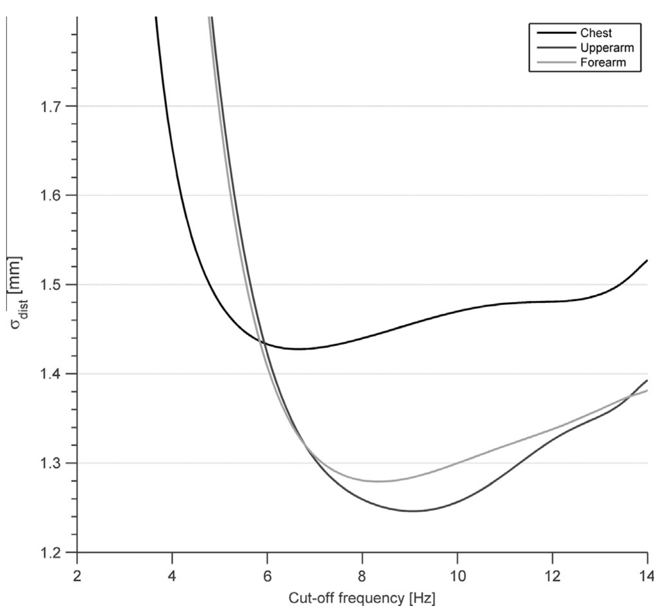

Fig. 7. The relationship between cut-off frequency and dynamic precision (σ_{dist}) for the experimental data of subject 2.

Table 2
Cut-off frequencies at which optimal dynamic precision (f_{dp}, in Hz) was found per rigid body in the experimental data. The number of kinematic data points in the signal is shown between brackets below the cut-off frequency. The cut-off frequency f_{dp} was found to be different between subjects and cluster positions.

Subject	Cut-off frequency (Hz) at lowest σ_{dist}		
	Chest	Upper arm	Forearm
1	5.7 ($n = 32$)	14.0 ($n = 28$)	10.4 ($n = 31$)
2	6.7 ($n = 30$)	9.1 ($n = 24$)	8.3 ($n = 30$)
3	4.6 ($n = 34$)	13.9 ($n = 23$)	10.0 ($n = 25$)
4	–[a]	6.6 ($n = 34$)	8.9 ($n = 36$)
5	13.2 ($n = 39$)	7.9 ($n = 28$)	11.1 ($n = 31$)

[a] In subject 4, the 3D position of the chest markers could not be reconstructed due to limited visibility of the markers.

4. Discussion

In the present study we examined the effect of filtering on the accuracy of a video-based 3D motion analysis system. In doing so, we focused on the underwater phase of the swimming stroke in view of the challenges it poses for accurate measurement. The effect of filtering data from a kinematic model with a cut-off frequency of 6 Hz, which was used in previous studies to filter underwater kinematic data, turned out to be dependent on cluster position and pull time. It was found that the commonly used procedure to filter position data using a fixed cut-off frequency for all the markers not always led to an improvement of the accuracy of the kinematic data, but could even decrease the accuracy. This result suggests that a good method for determining a filter frequency is needed.

The results from the model showed that by filtering with the cut-off frequency that leads to optimal dynamic precision per trial and per cluster position, the accuracy was improved irrespective of cluster position. Using this method, the accuracy was on average 29% better compared to the values based on the raw data. Therefore, the method to filter kinematic data using the cut-off frequency at which the variability in reconstructed distances between markers on a rigid body is lowest, led to improved accuracy. Filtering the data with the cut-off frequency that led to optimal accuracy resulted in an average improvement of 30% in accuracy, so the dynamic precision method yielded an improvement of about 97% of the maximal effect that can be achieved by filtering. In the present study we tested the dynamic precision method in a 'low precision' video based underwater motion analysis system; therefore the results we presented pertain to these conditions. However, in principle, the method could be applied in similar fashion to improve accuracy in a non-aquatic environment and when using 'high precision' motion analysis systems like Optotrak®.

The value for dynamic precision found in the experimental part of the present study is better than the precision obtained in dynamic conditions found by Ceccon et al. (2013). In the current study the coefficient of variation (the ratio of the standard deviation to the mean times 100%) was 2.90%. Ceccon et al. (2013) found a coefficient of variation of 7.58% for a 10 cm reference wand moving through the calibrated, underwater volume. Silvatti et al. (2013) compared different calibration procedures and found a coefficient of variation as low as 0.24% for a 3 m wand, which is much larger than the rigid body used in our study to calculate dynamic precision. In contrast to the aforementioned studies in which a wand was moved through the calibrated volume, we studied the precision during the underwater phase of the stroke. The motion of the wand might not mimic the swimming movement to a sufficient degree to determine the precision of the system achieved during the actual swimming stroke. The movement of the body parts through the water generates extra bubbles, which most likely increases reconstruction errors due to additional refraction. In addition, different calibration procedures (Silvatti et al., 2013), camera positions and camera resolutions could have caused differences in precision between studies. As pointed out by Figueiredo et al. (2011), the precision obtained in motion analysis systems for swimming is influenced by image distortion and by errors related to digitisation and 3D reconstruction (Payton and Bartlett, 1995; Kwon and Casebolt, 2006). We conclude that 3D motion analysis systems can be made more accurate by filtering the data using the cut-off frequency that yields optimal precision. Although we applied the dynamic precision method in the current study only to determine the optimal cut-off frequency in an aquatic environment, it can be used to optimise and evaluate other aspects of filtering (e.g. smoothing technique and filter order) and in any environment.

Bartlett (2007) already proposed to use different cut-off frequencies for different marker positions on the body. He argued that it is likely that swimming technique influences the frequency spectrum of the signal, which could explain the difference in optimal cut-off frequency between different positions on the body and their interaction with the subject (Bartlett, 2007). This could be why there was a significant effect of cluster position and pull time on the cut-off frequency resulting in optimal dynamic precision with our model simulations. Also the experimental data during actual swimming showed large variations in the cut-off frequency for optimal precision between cluster positions. The differences in motion between body segments and between subjects seem to result in different frequency spectra of the signals, which could lead to the differences in the optimal cut-off frequencies. Moreover, the fact that this optimal frequency differed considerably between subjects underscores that the filter frequency should be based on an assessment of the dynamic precision of the measurement system in question, and cannot, and should not, be based on a simple rule of thumb. However, whether it is feasible and necessary to apply this method per subject and per segment will most likely depend on the requirements of each study and is therefore the choice and responsibility of the researcher.

Conflicts of interest

The authors declare that there are no conflicts of interest.

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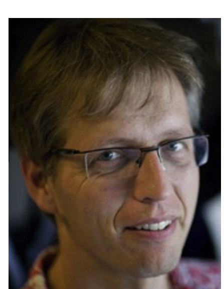

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