Estimation of single motor unit conduction velocity from surface electromyogram signals detected with linear electrode arrays

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Abstract—*This work addresses the problem of estimating the conduction velocity (CV) of single motor unit (MU) action potentials from surface EMG signals detected with linear electrode arrays during voluntary muscle contractions. In ideal conditions, that is without shape or scale changes of the propagating signals and with additive white Gaussian noise, the maximum likelihood (ML) is the optimum estimator of delay. Nevertheless, other methods with computational advantages can be proposed; among them, a modified version of the beamforming algorithm is presented and compared with the ML estimator. In real cases, the resolution in delay estimation in the time domain is limited because of the sampling process. Transformation to the frequency domain allows a continuous estimation. A fast, high-resolution implementation of the presented multichannel techniques in the frequency domain is proposed. This approach is affected by a negligible decrease in performance with respect to ideal interpolation. Application of the ML estimator, based on two-channel information, to ten firings of each of three MUs provides a CV estimate affected by a standard deviation of 0.5 m s^{-1}; the modified beamforming and ML estimators based on five channels provide a CV standard deviation of less than 0.1 m s^{-1} and allow the detection of statistically significant differences between the CVs of the three MUs. CV can therefore be used for MU classification.*

Keywords—*Electromyography, Linear electrode arrays , Beamforming, Maximum likelihood estimation, Motor unit action potentials, Muscle fibre conduction velocity estimation*

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1 Introduction

MUSCLE FIBRE conduction velocity (CV) is a basic physiological parameter and is known to be related to the type and diameter of muscle fibres, ion concentration, pH and motor unit (MU) firing rate (BRODY *et al*., 1991; HAKANSSON, 1956; MORIMOTO and MASUDA, 1984; NISHIZONO *et al*., 1989).

Several methods have been proposed to estimate CV from two surface EMG signals detected at a known distance along the muscle fibres (FARINA and MERLETTI, 2000; LO CONTE and MERLETTI, 1995; MERLETTI and LO CONTE, 1995). Most of them are global techniques: the estimated velocity is an average value computed from a signal epoch composed of a large number of MU action potentials (MUAPs) with different propagation velocities. Mean CV has been proven to be an important parameter to monitor muscle fatigue (MERLETTI *et al*., 1990; MERLETTI and DE LUCA, 1989).

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The identification and classification of single MUAPs from an interference EMG signal has been proven to be possible either manually (FARINA *et al*., 1998; MERLETTI *et al*., 1999) or using computer-assisted techniques (GAZZONI *et al*., 2000). Based on these results, an alternative technique to previous methods (DAVIES and PARKER, 1987) for the estimation of CV distribution has been recently proposed (FARINA *et al*., 2000). The method is based on the automatic identification of single MUAPs from an EMG interference signal detected with linear electrode arrays (MASUDA *et al*., 1985*a*,*b*; MASUDA and SADOYAMA, 1986; MERLETTI *et al*., 1999*c*; NISHIZONO *et al*., 1990), at least at moderate contraction levels.

An example of signals detected with a linear electrode array from the biceps brachii muscle during voluntary contractions, maintained at 25% and 50% of the maximum voluntary contraction (MVC), is reported in Fig. 1. It has been shown that single MUAPs can be identified for a large number of muscles with more complex anatomy than the biceps brachii muscle (BERGAMO *et al*., 1999).

The problem of estimating single MUAP CV from such signals has also been addressed recently by MUHAMMAD *et al*. (2000). The problem is related to that of estimating the delay between two or more signals travelling in the direction of the

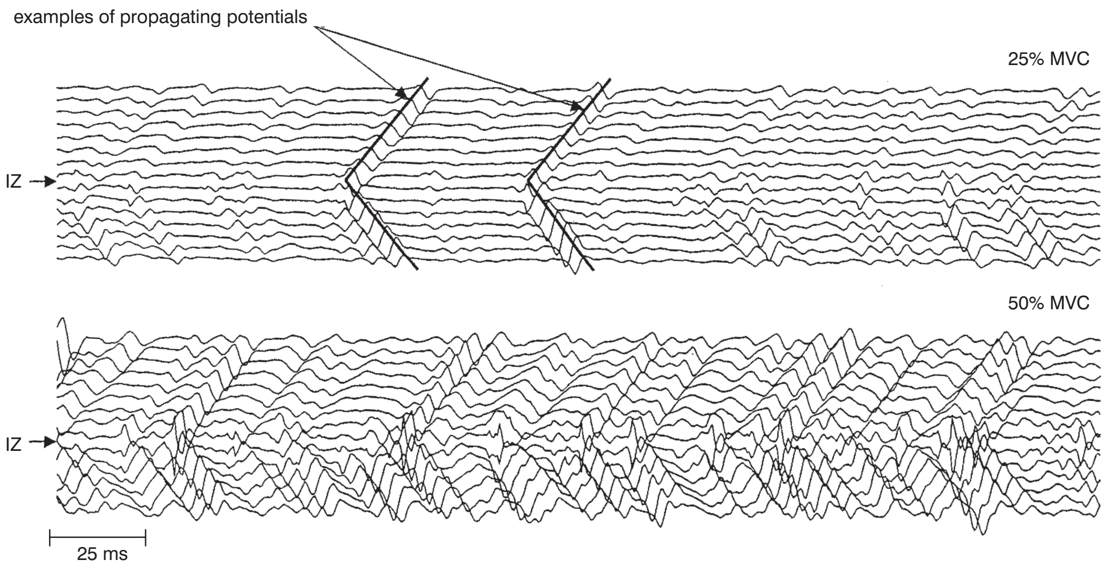

Fig. 1 *EMG signals detected with linear electrode array of 16 electrodes in single differential detection mode (interelectrode distance of 10 mm) from healthy biceps brachii muscle at two contraction levels. Propagating action potentials can be identified in interference signal (two are indicated in upper row). IZ = innervation zone*

detection electrodes. FARINA *et al.* (2000) proposed a beam-forming-based method, and MUHAMMAD *et al.* (2000) compared a maximum likelihood (ML) estimator with two-channel estimators for single MUAP CV estimation.

We compare these methods and propose an alternative fast, high-resolution algorithm to solve the problem of low resolution due to the sampling period, analysing the decrease in performance with respect to ideal interpolation. We show that the proposed fast, high-resolution, multichannel-based methods have considerably better performance in the case of additive white Gaussian noise and equally shifted signals compared with the traditional two-channel techniques. We focus our attention on single MUAP CV estimation, but we show that the methods can be effectively applied also for mean CV estimation.

The effects of end of fibre, end plate and inclination of the fibres with respect to the detection system on CV estimation, not investigated in the literature for the case of multichannel detection, are also addressed. Some preliminary indications in this context are given in recent modelling studies by MERLETTI *et al.* (1999*a*,*b*) for two channel-based CV estimators. We extend these results, with a number of simulated examples, to multichannel-based methods.

2 Methods

2.1 *Simulation method*

A physical model of EMG generation has been previously developed (FARINA and MERLETTI, 2001). The model takes into account the volume conductor as a layered and anisotropic medium (muscle, fat and skin tissues), the end-plate and end-of-fibre effects, electrode shape and size.

Accurate simulation of the MUAP generation, propagation and extinction is very important for identifying aspects often neglected in works focused on muscle fibre CV estimation, as will be shown in the following.

Default values used for the generation of all the synthetic signals in this paper are reported in Table 1 and refer to the description given by FARINA and MERLETTI (2001). In all the simulations, MUs have been assumed to have a single muscle fibre. The inclusion of a model of the MU with a given territory would introduce a number of additional parameters (such as the size of the territory, the distribution of the fibres in the territory, the distribution of the end plates and tendons etc.) that would add confounding factors and mask basic relationships that are outlined in this work. For the same reason, only point-recording electrodes have been simulated.

Table 1 Parameter values chosen to simulate all synthetic signals used in this work

Parameter	Description	Default value
R_c	conductivity ratio between skin and fat layer	20
R_m	conductivity ratio between fat layer and muscle along direction transversal to fibre direction	0.5
R_a	conductivity ratio between muscle in fibre direction and muscle along direction transversal to fibre direction	5
h	thickness of fat layer	3 mm
d	thickness of skin layer	1 mm
$I(z)$	intra-cellular current density source	$Az^3e^z - B$ (Rosenfalck's expression)
f_{samp}	sampling frequency	1024 Hz
Dectection system	spatial filter used for signal detection	double differential technique
N_{fib}	number of fibres in an MU	1
$H_{size}(k_x, k_z)$	equivalent transfer function of electrode shape and size (in spatial frequency domain)	1 (point electrodes)
v	conduction velocity of MUs	4 ms^{-1}

2.2 *Delay estimators based on multiple detection points*

In ideal conditions, K observed signals are available that are shifted versions of a signal $s(t)$ embedded in different independent, white, zero mean, additive Gaussian noises $w_k(t)$ with equal variance σ^2. We therefore have the random processes $x_k(t)$ given by

$$x_k(t) = s(t-(k-1)\theta) + w_k(t) \qquad k = 1, \ldots, K; \quad 0 \le t \le T \tag{1}$$

where θ is the delay between adjacent channels.

The maximum likelihood estimation (MLE) of the time delay θ implies the minimisation of the error

$$e_{MLE}^2 = \sum_{k=1}^{K}\sum_{n=1}^{N}[x_k(n) - s(n-(k-1)\theta)]^2 \tag{2}$$

where N is the number of samples in the epoch of duration T, considering the time in discrete form.

As $s(n)$ is unkown, the minimisation of e_{MLE}^2 is possible with an estimate $\hat{s}(n)$ of $s(n)$

$$\hat{s}(n) = \frac{1}{K}\sum_{m=1}^{K} x_m(n+(m-1)\theta) \tag{3}$$

Replacing the real signal by the estimated $\hat{s}(n)$ in eqn 2 leads to

$$\begin{aligned} e_{MLE}^2 &= \sum_{k=1}^{K}\sum_{n=1}^{N}\left[x_k(n) - \frac{1}{K}\sum_{m=1}^{K} x_m(n+(m-k)\theta)\right]^2 \\ &= \sum_{k=1}^{K}\sum_{n=1}^{N}\left[x_k(n) - \frac{1}{K}x_k(n) - \frac{1}{K}\sum_{m=1,m\neq k}^{K} x_m(n+(m-k)\theta)\right]^2 \\ &= \left(1-\frac{1}{K}\right)\sum_{k=1}^{K}\sum_{n=1}^{N}\left[x_k(n) - \frac{1}{K-1}\sum_{m=1,m\neq k}^{K} x_m(n+(m-k)\theta)\right]^2 \end{aligned} \tag{4}$$

Minimisation of eqn 4 with respect to θ is equivalent to the minimisation of the summation of K mean square errors with respect to the same parameter θ

$$e_{MLE}^2 = \sum_{k=1}^{K} e_k^2 \tag{5}$$

with

$$e_k^2 = \sum_{n=1}^{N}\left[x_k(n) - \frac{1}{K-1}\sum_{m=1,m\neq k}^{K} x_m(n+(m-k)\theta)\right]^2 \tag{6}$$

Minimisation of e_k^2 results in the delay that minimises the sum of the mean square errors between the signal $x_k(n)$ (later referred to as reference signal) and the average of the other resynchronised signals. The conventional beamforming delay estimation (Johnson and Duolgeon, 1993) is based on a maximum energy deduction criterion. In the case of unidirectionally propagating signals, the estimated delay with the beamforming approach is the value that maximises the energy of the average of all the aligned signals. In the case described by eqn 6, the mean square error between a reference signal and the other aligned signals is minimised (modified beamforming). From eqn 5, it is clear that the MLE is the minimisation of the sum of the mean square errors obtained by performing this modified beamforming, with all the signals in the array taken as reference one after another.

The minimisation of the mean square error in the discrete time domain will lead to a delay resolution limited by the sampling period. Hence, an interpolation technique is required. The frequency-domain approach provides a solution to this problem (McGill and Dorfman, 1984). Eqn 6 can, in fact, be re-written in the frequency domain, where the delay is a continuous variable, and no resolution limit is imposed. Farina *et al.* (2000) adopted this approach for beamforming-based estimation with an exhaustive search for the optimum delay (that is, by computing e_k^2 for a number of values of θ and selecting the θ value corresponding to the lowest e_k^2), and Muhammad *et al.* (2000) proposed an interpolation of the cross-correlation function around its peak value with a second-order polynomial function. In the following, we propose a fast detection of the minimum of e_k^2 and e_{MLE}^2, based on the iterative Newton method.

If we consider $k=1$, we can write eqn 6 in the frequency domain as

$$e_1^2 = \frac{2}{N}\sum_{\alpha=1}^{N/2}\left|\frac{1}{K-1}\sum_{i=2}^{K} X_i(\alpha)e^{j2\pi\alpha(i-1)\theta/N} - X_1(\alpha)\right|^2 \tag{7}$$

where N is the number of samples of the signals in the epoch considered.

Eqn 7 can be then written in the form

$$\begin{aligned} e_1^2 = \frac{2}{N}\sum_{\alpha=1}^{N/2}\Bigg[&\frac{1}{(K-1)^2}\sum_{i=2}^{K}|X_i(\alpha)|^2 \\ &+ \frac{2}{(K-1)^2}\sum_{i=2}^{K}\sum_{w=i+1}^{K}\mathrm{Re}\{X_i(\alpha)X_w^*(\alpha)e^{j2\pi\alpha(i-w)\theta/N}\} \\ &+ |X_1(\alpha)|^2 \\ &- 2\mathrm{Re}\left\{X_1^*(\alpha)\frac{1}{K-1}\sum_{i=2}^{K}X_i(\alpha)e^{j2\pi\alpha(i-1)\theta/N}\right\}\Bigg] \end{aligned} \tag{8}$$

which is the expression used for the following calculations and where * indicates the complex conjugate.

The computational time required for an exhaustive search for the minimum of e_1^2 would be considerable, and resolution would be limited by the step chosen; in fact, a limited step of θ for the computation of e_1^2 must be considered in practice. A better approach would be to find the minimum of the mean square error by finding the zero of its first derivative by an iterative technique, such as the Newton method (Press and Vetterling, 1996). This approach has been already applied elsewhere (McGill and Dorfman, 1984) for the case of two delayed signals. The extension of the technique for modified beamforming and MLE is derived below.

The first derivative of e_1^2 with respect to the delay θ is given by

$$\begin{aligned} \frac{de_1^2}{d\theta} = \frac{4}{N}\sum_{\alpha=1}^{N/2}\mathrm{Im}\Bigg\{&X_1^*(\alpha)\frac{1}{K-1} \times \sum_{i=2}^{K}X_i(\alpha)\frac{2\pi\alpha(i-1)}{N}e^{j2\pi\alpha(i-1)\frac{\theta}{N}} \\ &- \frac{1}{(K-1)^2}\sum_{i=2}^{K}\sum_{w=i+1}^{K}X_i(\alpha)X_w^*(\alpha) \times \frac{2\pi\alpha(i-w)}{N}e^{\frac{j2\pi\alpha(i-w)\theta}{N}}\Bigg\} \end{aligned} \tag{9}$$

and the second derivative is given by

$$\frac{d^2 e_1^2}{d\theta^2} = \frac{4}{N}\sum_{\alpha=1}^{N/2} \mathrm{Re}\left\{ X_1^*(\alpha)\frac{1}{K-1}\sum_{i=2}^{K} X_i(\alpha) \times \left(\frac{2\pi\alpha(i-1)}{N}\right)^2 e^{j2\pi\alpha(i-1)\frac{\theta}{N}} - \frac{1}{(K-1)^2}\sum_{i=2}^{K}\sum_{w=i+1}^{K} X_i(\alpha)X_w^*(\alpha) \times \left(\frac{2\pi\alpha(i-w)}{N}\right)^2 e^{\frac{j2\pi\alpha(i-w)\theta}{N}} \right\} \quad (10)$$

The iterative Newton formula can then be applied

$$\theta_{l+1} = \theta_l - \frac{\frac{de_1^2}{d\theta}\big|_{\theta_l}}{\frac{d^2 e_1^2}{d^2\theta}\big|_{\theta_l}} \quad l = 0, 1, \ldots \quad (11)$$

Starting from a 'reasonable' θ_0 (as discussed below), eqn 11 will converge to the optimum delay.

The case of modified beamforming with a reference signal other than $x_1(t)$ is easily obtained from the case $k = 1$. On the other hand, MLE implies the minimisation of e_{MLE}^2. By differentiating both sides of eqn 5, we obtain

$$\frac{de_{MLE}^2}{d\theta} = \sum_{k=1}^{K}\frac{de_k^2}{d\theta}$$

and

$$\frac{d^2 e_{MLE}^2}{d\theta^2} = \sum_{k=1}^{K}\frac{d^2 e_k^2}{d\theta^2}$$

where $de_k^2/d\theta$ and $d^2e_k^2/d\theta^2$ are derived from eqns 9 and 10, respectively. Substitution of these expressions into eqn 11 provides the iterative solution in the case of MLE.

The well-known problem of local minima (related to the starting point θ_0) (Bonato *et al.*, 1990) arises, especially when the signal-to-noise ratio (SNR) is poor, so that a decrease in performance with respect to exhaustive searching is expected. Some solutions to this problem have been proposed in the literature (Press and Vetterling, 1996). They can be grouped in three main classes based on

(a) finding local minima associated with varying starting values (may be chosen randomly) and then selecting the lowest,
(b) perturbing a local minimum by taking a step away from it and then seeing if the routine returns to a different point,
(c) calculating a coarse estimation of the absolute minimum and then refining the estimation using the coarse estimate as a starting point.

Following the last approach, a coarse estimation of the delay can be obtained by calculating the cross-correlation between two of the signals of the array. If the propagation direction is known, it is sufficient to limit the coarse search to delays within the physiological limits corresponding to a CV between 2 m s^{-1} and 7 m s^{-1} (for example, in the case of a sampling rate of 1 kHz and interelectrode distance of 10 mm, a search between one and five lags is required). A coarse estimation will then be obtained by the computing of a few lags (depending on the sampling frequency and interelectrode distance) of the cross-correlation of two of the signals of the array and interpolation around its peak value with a parabola.

2.3 *Selection of reference signal with distribution function method*

In ideal conditions of equally delayed versions of the same signal embedded in white Gaussian noise, MLE gives the best performance. In the non-ideal case, the propagating signals of the array do not have the same shape. The most important reasons for shape differences are inclination of the fibres with respect to the detection array and end-of-fibre and end-plate effects (Merletti *et al.*, 1999*a*,*b*). These effects have rarely been taken into account in the comparison of two-channel algorithms for CV estimation from EMG signals and never in the case of multichannel techniques. In the case of finite-length fibres inclined with respect to the array, the analytical simplification given by eqn 1 is not valid.

The effect of a change in shape on CV estimation is very difficult to predict analytically as it depends on a number of factors, such as the physical properties of the volume conductor (Merletti *et al.*, 1999*a*; Schneider *et al.*, 1991), the depth of the MU, the detection system or the length of the fibres. A physical model of EMG generation is thus required and is crucial for validation of delay estimator performance.

A decrease in performance is expected when more than two channels are used for CV estimation, because shape differences can be large for distant detection points while negligible for adjacent channels. It can be expected that, by using the beamforming-based method and selecting the reference signal to minimise the average shape difference with the other signals, a better estimation with respect to MLE can be obtained.

To minimise the effect of non-ideal conditions on CV estimation, we thus propose to apply modified beamforming, taking the reference signal as explained above. Moreover, a definition of distance has to be chosen. For this purpose, different criteria can be used. Shape difference estimation by correlation coefficient is a candidate, but complication arises when there is a time-scale factor between the signals.

The distribution function method (DFM) (Rix and Malengé, 1980; Rix and Meste, 1997) is an alternative approach to evaluate the similarity in shape between scaled and delayed signals. The DFM is based on the invariance of the distribution function (DF) of a signal for any transformation of the type

$$p_1(t) \longrightarrow p_2(t) = Cp_1[\phi^{-1}(t)]\frac{d}{dt}\phi^{-1}(t) \quad (12)$$

where C is a constant and $\phi(\cdot)$ is an increasing continuous function. It has been shown (Rix and Malengé, 1980) that the DFs of two signals are equal in abscissa values x and y related by $y = \phi(x)$. On the other hand, two signals $s_1(t)$ and $s_2(t)$ are equal in shape if we can write a relationship of the form

$$s_1(t) = Cs_2\left(\frac{t-\theta}{a}\right) \quad a > 0$$

which is the same as choosing $\phi(t) = at + \theta$ in eqn 12. In the case of no scale and shape changes, we obtain the line $\phi(t) = t + \theta$ $(a = 1)$. The distance of the computed curve $\phi(t)$ from this ideal line can be considered a measure of the distance between signals that contain the scale and shape difference. Fig. 2 reports two examples of simulated signals and the calculation of the DF-based distance. MUAPs generated by an MU in the case of alignment and of inclination of the fibres with respect to the detection array are shown. In both cases the lateral distance between the centre of the array and the fibre is zero. Cross-correlation function and function $\phi(t)$ for two signals of the array (indicated by bold lines) are shown for the two cases. The correlation coefficient CC and the distance computed with DFM d_{DFM} are reported. It appears that the correlation coefficient is not sensitive to small-scale changes (its value is almost the same in the two cases), whereas scale change

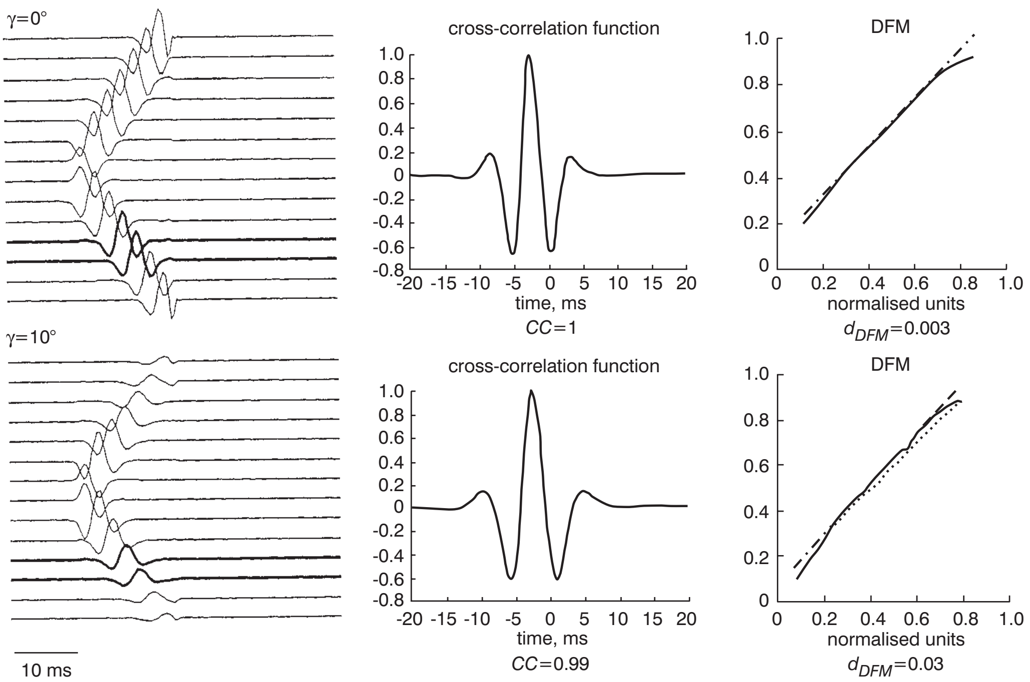

Fig. 2 *Examples of synthetic MUAPs generated by MU in case of alignment and of inclination of fibres with respect to detection array. (——) Computed function $\phi(t)$; (–·–) regression line; (·····) ideal regression line $(t+\theta)$ for the two cases*

due to fibre inclination is detected by DFM (note the difference in d_{DFM} values and between ideal $\phi(t)$ and the computed regression line).

Note that the proposed measure of distance can also be used for the selection of a subset of signals of the array for CV estimation. This can be useful in the case of artefacts in the signal. To do so, it is possible to compute the matrix of distances between the signals; the element (i,j) of this matrix is the distance between signal i and signal j of the array. From the matrix of distances, it is possible to classify the signals and disregard those too different from the others, for example using a minimum spanning tree-based algorithm (THEODORIDIS and KOUTROUMBAS, 1999).

3 Results

3.1 *Infinite fibres aligned with respect to the detection system*

Fig. 3 shows the results obtained for a simulated MUAP generated by an infinite fibre (aligned with the detection system) as a function of SNR in the case of CV estimation using only two channels of the array. 200 simulations for each SNR value were performed. For the results reported in this and in all the following figures, exhaustive searching was performed by selecting a CV range between 2 and $7\,\mathrm{m\,s^{-1}}$ and a step of θ leading to an absolute error in CV estimation of $0.01\,\mathrm{m\,s^{-1}}$ in the case of a CV value of $4\,\mathrm{m\,s^{-1}}$.

The mean squared error (MSE) of the estimate of CV has been chosen as a performance parameter. It is defined as

$$\mathrm{MSE} = \sigma^2 + B^2 \tag{13}$$

where σ^2 is the variance of the estimate and B is the bias.

Fig. 4 shows the same results for estimations obtained from seven channels with beamforming (Fig. 4*a*) and MLE (Fig. 4*b*).

The two-channel delay estimator (Fig. 3) is not much affected by the starting point, whereas beamforming and MLE are more sensitive to this value, and the estimate may not converge to the correct value when the starting point is too different from it. For multi-channel-based methods, it appears that introducing a coarse estimation of the delay improves, on average, the performance compared with that obtained by assuming a random starting point. It is deduced that the number of local minima increases with the number of channels.

Fig. 5 compares the exhaustive searching and the iterative procedure for beamforming and ML techniques and for different number of channels. At 10 dB SNR, the performance of the beamforming method with the first signal as reference decreases if more than seven channels are selected, whereas the performance of MLE starts to decrease with more than nine channels. The limit is, in any case, acceptable for EMG applications in which it is difficult to obtain more than 6–7 signals propagating unidirectionally (Fig. 1).

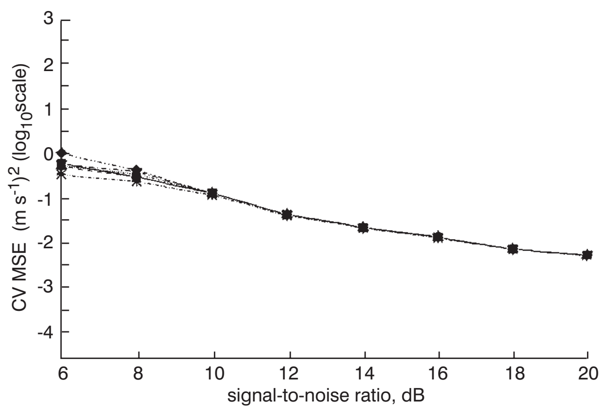

Fig. 3 *Comparison of MSE (eqn 13) of CV estimations obtained from two signals (traditional spectral matching algorithm proposed by McGILL and DORFMAN (1984)) in case of exhaustive searching (ideal) and in case of iterative procedure with different starting points (v_c is coarse estimation of CV by means of cross-correlation) and SNRs. (-■-) Start = $2\,\mathrm{m\,s^{-1}}$; (-·●-·) start = $3\,\mathrm{m\,s^{-1}}$; (··▲··) start = $4\,\mathrm{m\,s^{-1}}$; (-·▼-·) start = $5\,\mathrm{m\,s^{-1}}$; (-·◆-·) start = $6\,\mathrm{m\,s^{-1}}$; (··×··) start = v_c; (-·*-·) ideal. Two hundred simulations for each SNR value have been performed. "Ideal" results in this and in the following figures are obtained by exhaustive searching in the CV range $2\,\mathrm{m\,s^{-1}}$ to $7\,\mathrm{m\,s^{-1}}$ using a step of θ leading to an absolute error $< 0.01\,\mathrm{m\,s^{-1}}$ for CV = $4\,\mathrm{m\,s^{-1}}$*

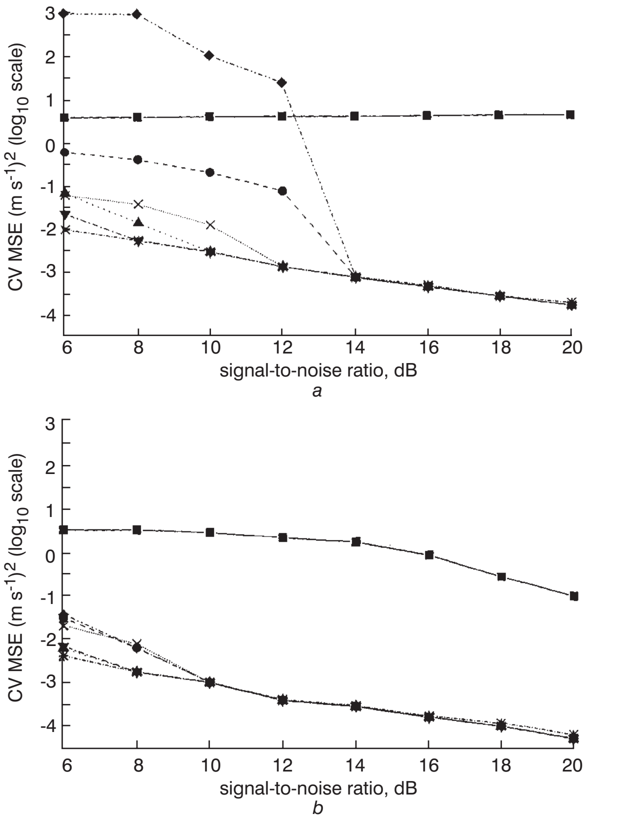

Fig. 4 *Comparison of MSE (eqn 13) of CV estimations obtained from seven signals in case of exhaustive searching (ideal) and in case of iterative procedure with different starting points (v_c is coarse estimation of CV by means of cross-correlation); results obtained with (a) beamforming technique with first channel ($k = 1$ in eqn 1) as reference and (b) MLE are shown. Two hundred simulations for each SNR value were performed. Note that, for particular choices of starting value, MSE is very high or even almost independent of SNR. This clearly indicates presence of local minima. (–■–) Start = 2 m s^{-1}; (- -●- -) start = 3 m s^{-1}; (··▲··) start = 4 m s^{-1}; (-·▼-·) start = 5 m s^{-1}; (-·◆-·) start = 6 m s^{-1}; (··×··) start = v_c; (-··∗-·) ideal*

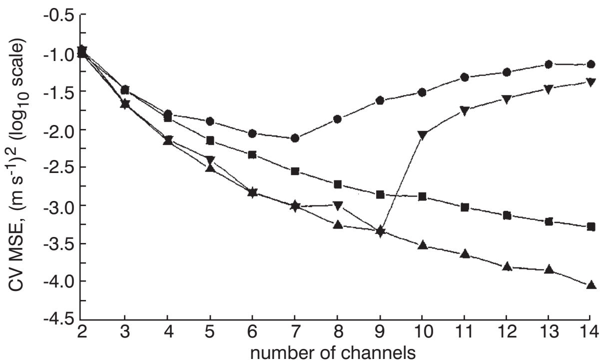

Fig. 5 *MSE (eqn 13) of CV estimations as function of number of channels in case of exhaustive searching (ideal) and in case of iterative procedure with coarse estimation of starting point for beamforming (first signal as reference) and MLE, at 10 dB SNR. Two hundred simulations were performed for each number of channels. (–■–) Beam 1 (ideal); (–●–) beam 1 (coarse estimation of θ_0); (–▲–) MLE (ideal); (–▼–) MLE (coarse estimation of θ_0)*

Fig. 6 reports the comparison of all the proposed techniques in the case of iterative procedure with the starting coarse estimation of the delay. MLE shows the best performance, but it requires a computational time about K times longer than that for beamforming-based techniques. Note that the performance of the beamforming-based method strongly depends on the choice of the reference signal. In particular, the beamforming-based method with the middle signal as reference performs worse than the two-channel estimator, whereas, if the first channel (corresponding to $k = 1$ in eqn 1) is chosen as reference, the performance obtained is close to that of MLE.

3.2 *Effect of inclination and finite length of fibres on single MUAP CV estimation*

Fig. 7 shows a few examples of CV estimation as a function of the inclination angle in the case of infinite-length fibres (no generation or end effect) for simulated MUAPs at different positions in the muscle. In particular, x_0 indicates the distance over the skin plane between the centre of the array and the MU, and y_0 is the depth of the MU in the muscle. Traditional two-channel estimations are compared with the beamforming estimation with reference signal selected by DFM, as previously described.

Note that CV can be over-estimated, as well as under-estimated, when the angle of inclination increases, and this is owing to the fact that anisotropy of the tissues causes shape and scale changes in the double differentially detected signals. Such changes are more evident for deep MUs (large y_0 values; Fig. 7*d*).

It appears that modified beamforming with DFM, in general, does not lead to estimations with higher bias than the two channel-based algorithm, whereas the application of MLE (Fig. 8) can lead to high bias also at moderate angles of inclination.

Fig. 9 reports results obtained when finite-length fibres are simulated. The well-known effect of an increase in CV estimation when the electrodes are close to the end plate or to the tendons (Roy *et al*., 1986; Merletti *et al*., 1999*a*,*b*) is evident. It is also clear that the phenomenon is more pronounced for fibres far from the detection electrodes. Beamforming with DFM and ML perform almost equivalently and give results comparable with those of two-channel techniques, even if all the available propagating signals, from the neuromuscular junction (NMJ) to the tendon, are used for the estimation.

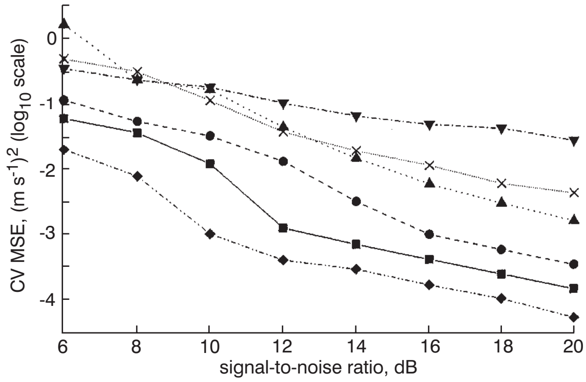

Fig. 6 *Comparison of MSE (eqn 13) of CV estimations obtained from seven signals in case of iterative procedure with starting point selected with cross-correlation for all presented methods; results of two-channel delay estimation are also shown. Results obtained with beamforming are reported for four choices of reference signal corresponding to first four signals ($k = 1, \cdots, 4$ in eqn 1) used for estimation. Two hundred simulations for each SNR value were performed. (–■–) Beam 1; (- -●- -) beam 2; (··▲··) beam 3; (-·▼-·) beam 4; (-·◆-·) MLE; (··×··) two-channel estimation*

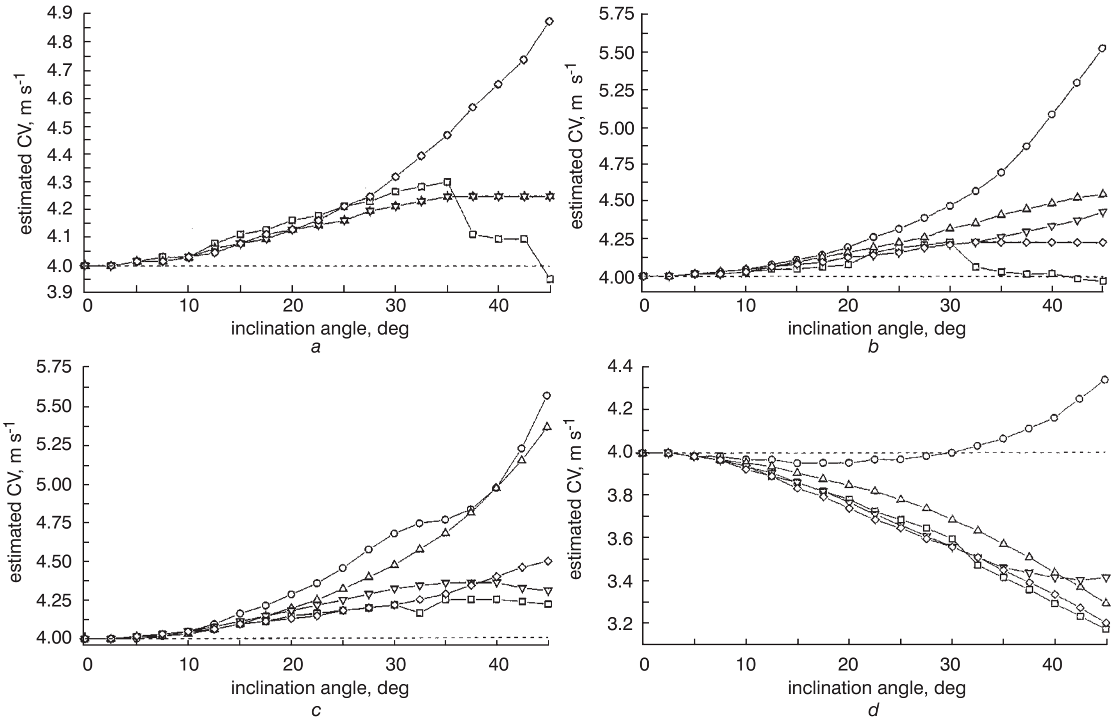

Fig. 7 *Single MUAP CV estimations as function of angle of inclination of fibres with respect to detection array in case of two-channel estimation and in case of beamforming estimation (using 5 channels) with DFM-based reference selection for different positions of fibres in muscle. y_0 depth of MU in muscle; x_0 distance, over skin plane, between fibre and centre of array. In case of two-channel method, four estimations corresponding to four choices of couple of adjacent DD signals are shown. (–□–) Beam with DFM; (–○–) double 1; (–△–) double 2; (–▽–) double 3; (–◇–) double 4; (- - -) correct value. (a) Infinite length fibre, $x_0 = 0$ mm, $y_0 = 1$ mm; (b) infinite length fibre, $x_0 = 5$ mm, $y_0 = 1$ mm; (c) infinite length fibre, $x_0 = 10$ mm, $y_0 = 1$ mm; (d) infinite length fibre, $x_0 = 5$ mm, $y_0 = 7$ mm*

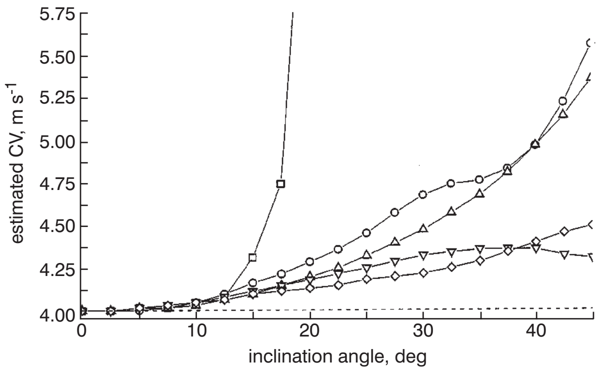

Fig. 8 *Single MUAP CV estimations as function of angle of inclination of fibres with respect to detection array in case of two-channel estimation and in case of MLE (using 5 channels) for particular position of fibre in muscle. y_0 = depth of MU in muscle; x_0 = distance, over skin plane, between fibre and centre of array. In case of two-channel method, four estimations corresponding to four choices of couple of adjacent DD signals are shown. Infinite length fibre, $x_0 = 10$ mm, $y_0 = 1$ mm. (–□–) MLE; (–○–) double 1; (–△–) double 2; (–▽–) double 3; (–◇–) double 4; (- - -) correct value*

It must be noted that the two channel-based method has lower bias compared with multichannel techniques if the detection position is in the middle between the NMJ and the tendon. The difference is negligible, in practice, if the channels used for CV estimation correspond to electrodes at a distance of a few millimetres from the innervation and tendon zone (Figs 9*c* and *d*).

Fig. 10 reports similar results in the case of a short fibre and interelectrode distance of 5 mm. It is evident that the bias in CV estimation is higher in this case, both for two-channel and for multi-channel techniques, but similar conclusions as in the previous case can be drawn.

3.3 *Experimental results*

Multi-channel techniques have been compared with two-channel methods for single MUAP CV estimation in real signals detected from the biceps brachii muscle. EMG signals were detected during a voluntary isometric contraction at 10% MVC with a linear electrode array of 16 electrodes (silver bars, 10 mm long, 10 mm apart, 1 mm diameter). The array was placed on the skin after a few trials to obtain the most similar propagating signals in the two directions from the NMJ to the tendons (based on visual observation).

The signals were amplified with a 10–450 Hz bandwidth (40 dB per decade slope on each side) and were sampled at 2048 Hz. The samples were digitised by a 12 bit A/D converter.

Isolated firings of three different MUs were identified by computer-assisted analysis, as reported by Merletti *et al.* (1999*c*). In total, ten firings for each MU were classified (Fig. 11); the classification criterion was based on mean square error between the entire pattern of the 15 single differential (SD) waveforms detected. Double differential (DD) signals were computed off-line from the SD signals and used for CV estimation. Five DD signals were used for CV estimation in the case of multichannel techniques (Fig. 11). As the contraction lasted for less than 10 s at a very low contraction level (10% MVC), we assume that no changes occured in the CV of the MUs involved in the contraction (no myoelectric manifestations of muscle fatigue).

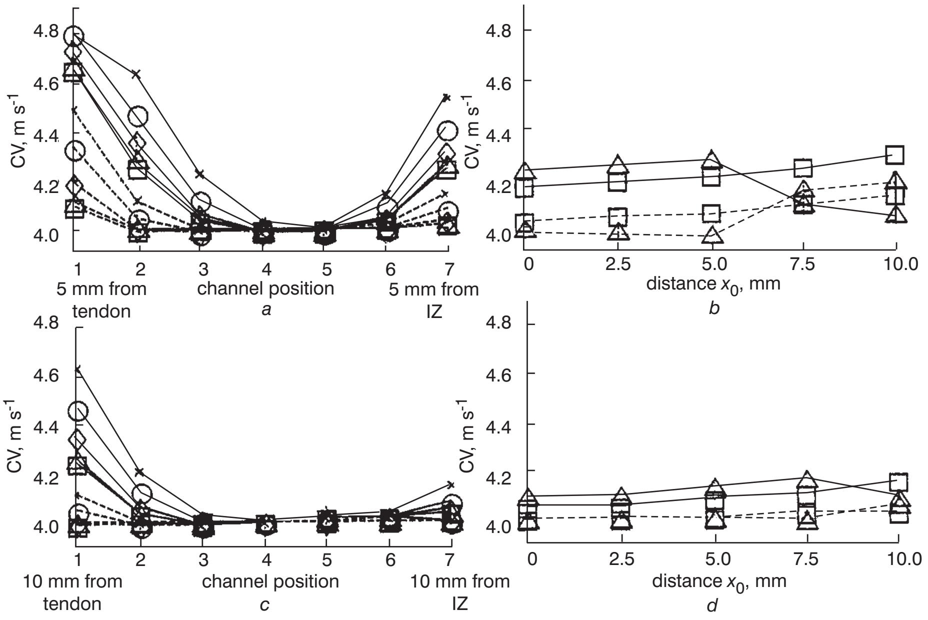

Fig. 9 *CV estimations in case of finite length fibres with (a,c) two-channel method, and (b,d) beamforming with DFM and MLE using five channels for two semilengths of fibres (70 mm and 80 mm, respectively). Correct CV* $= 4\,m\,s^{-4}$. *NMJ and tendon are at distance of (a,b) 5 mm and (c,d) 10 mm from first and last electrode of array, respectively. MU is at depths of (—) 7 and (- - -) 3 mm in muscle and is aligned with detection array. Interelectrode distance* $d_e = 10\,mm$. *(a,c) (□)*$x_0 = 0\,mm$; *(△)* $x_0 = 2.5\,mm$; *(◇)* $x_0 = 5\,mm$; *(◯)* $x_0 = 7.5\,mm$; *(×)* $x_0 = 10\,mm$. *(b,d) (□) MLE; (△) beamforming with DFM*

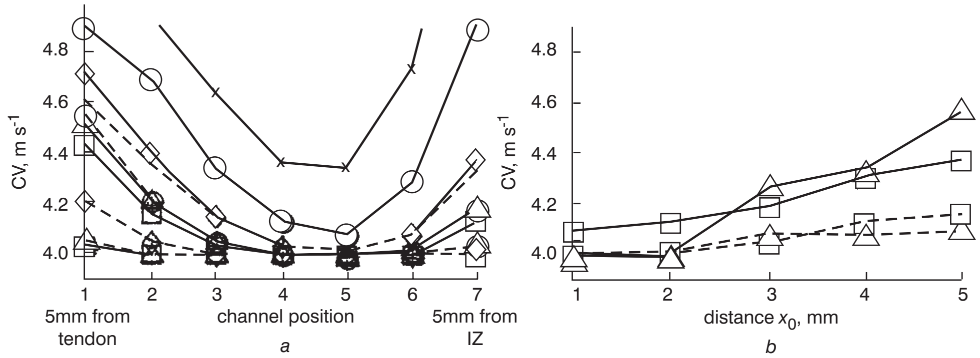

Fig. 10 *CV estimations in case of finite-length fibres with (a) two channel method, and (b) beamforming with DFM and MLE using five channels for fibre of semilength 40 mm, at depths of 3 mm and 1 mm in muscle, aligned with detection array. NMJ and tendon are at distance of 5 mm from first and last electrode of array, respectively. Interelectrode distance* $d_e = 5\,mm$. *Correct CV* $= 4\,m\,s^{-1}$ *(a) (□)* $x_0 = 0\,mm$; *(△)* $x_0 = 2.5\,mm$; *(◇)* $x_0 = 5\,mm$; *(◯)* $x_0 = 7.5\,mm$; *(×)* $x_0 = 10\,mm$. *(b) (□) MLE; (△) beamforming with DFM*

Assuming a correct classification of the firings, there should be no variability between CV estimations from the different firings of the same MU. We have applied the proposed techniques for the computation of the CV for all the detected firings for each MU and we have compared the results obtained with the traditional two channel-based techniques (Fig. 12).

It appears that the variance of estimation of CV makes it impossible to distinguish between the CVs of the three MUs if two channel-based techniques are used. In the case of multichannel techniques, the variance of estimation decreases considerably and permits us statistically to distinguish the three MUs on the basis of their CV. MLE and beamforming perform almost in the same way, with a lower variance in the case of MLE, as expected. No significant difference was found in the mean CV for the three MUs between the two multichannel-based techniques, as was expected in the case of negligible inclination of the muscle fibres. It is worth noting that, in the case of the biceps brachii, the muscle fibres are parallel, and the problem of fibre inclination is probably of minor importance. It is, in fact, evident from the simulation results that all the techniques have similar bias when fibre inclination is up to 10°.

Although we focus our attention on single MUAP CV estimation, the proposed techniques can be also applied for mean CV estimation, improving the performance obtained with traditional two-channel estimations. Fig. 13*b* shows two representative examples of application of the iterative MLE to real signals. The results concern the estimation of mean CV from signal epochs of 0.25 s. The signals have been collected again from the biceps brachii muscle with a linear array of 16 electrodes and interelectrode distance of 10 mm, using the SD detection technique (DD signals were then computed off-line and used for CV estimation). Six channels with unidirectional propagation were selected for MLE. An epoch of the signals used for CV estimation is shown in Fig. 13*a*. The improvement obtained by performing MLE with six channels, compared with the use of two channels, is evident also in the case of mean CV estimation.

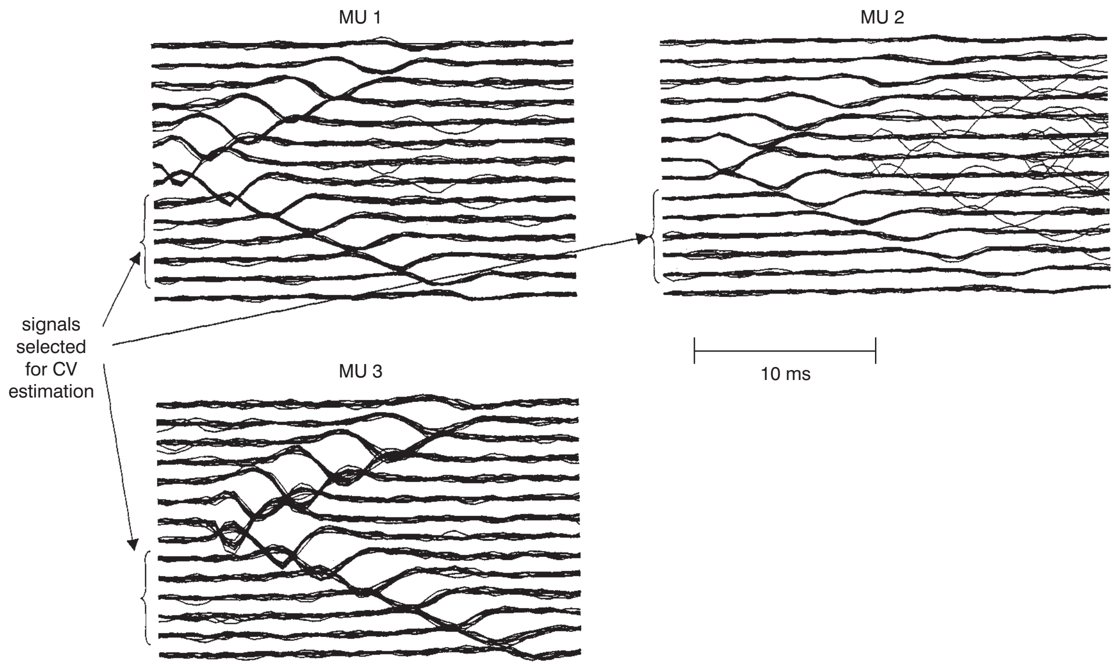

Fig. 11 *MUAPs detected with linear array of 16 electrodes from biceps brachii muscle (isometric contraction at 10% MVC) and classified as belonging to three different MUs on basis of their morphology. Ten firings for each MU, not significantly superimposed with others, have been detected. DD signals are shown*

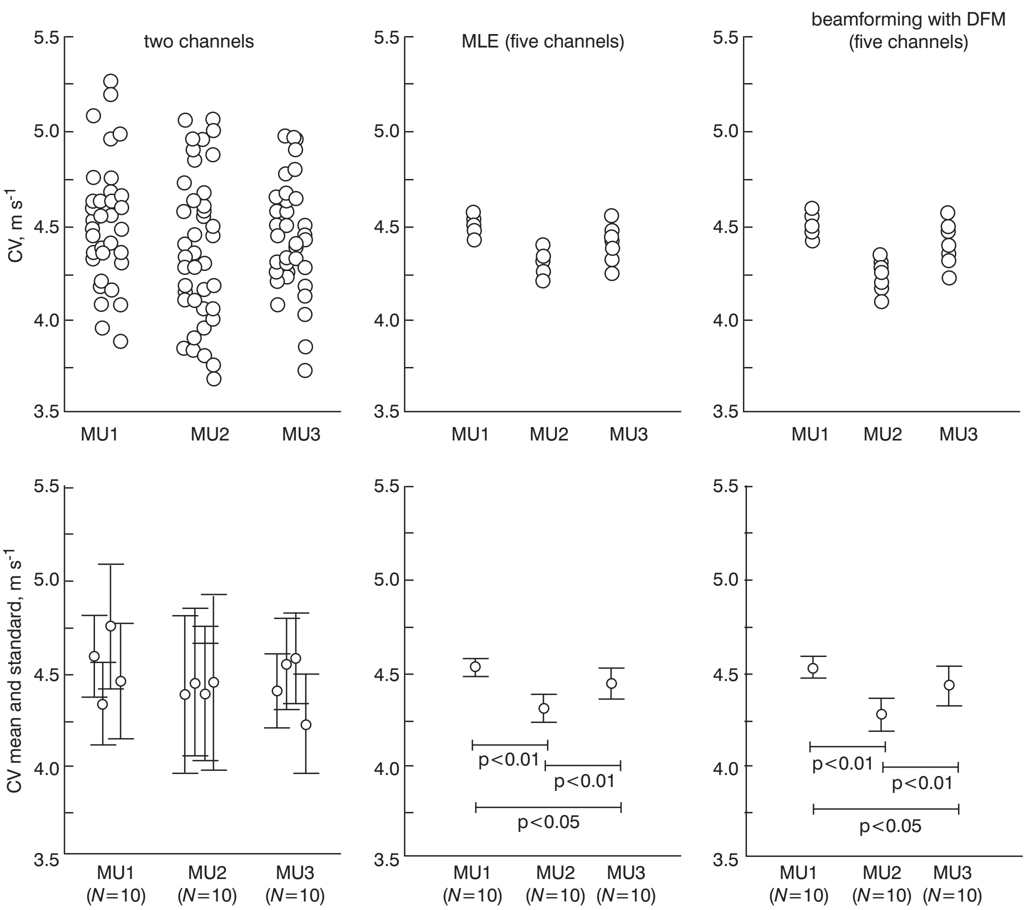

Fig. 12 *Results of application of two-channel estimator, MLE and beamforming with DFM to MUAPs shown in Fig. 11. CV has been computed from all detected firings of three MUs with two or five DD signals (in case of MLE and beamforming). In case of two-channel estimation, four estimations obtained using four couples of adjacent signals are reported for each firing. In lower row, mean and standard deviation of 10 estimations for each MU are reported for three techniques. p value resulting from Student t-test for independent samples is shown for multichannel methods and is related to comparison between CV values of the three MUs. It appears that the three MUs have statistically different CV estimates if multichannel techniques are used. In the case of the two-channel method, no significant difference can be observed*

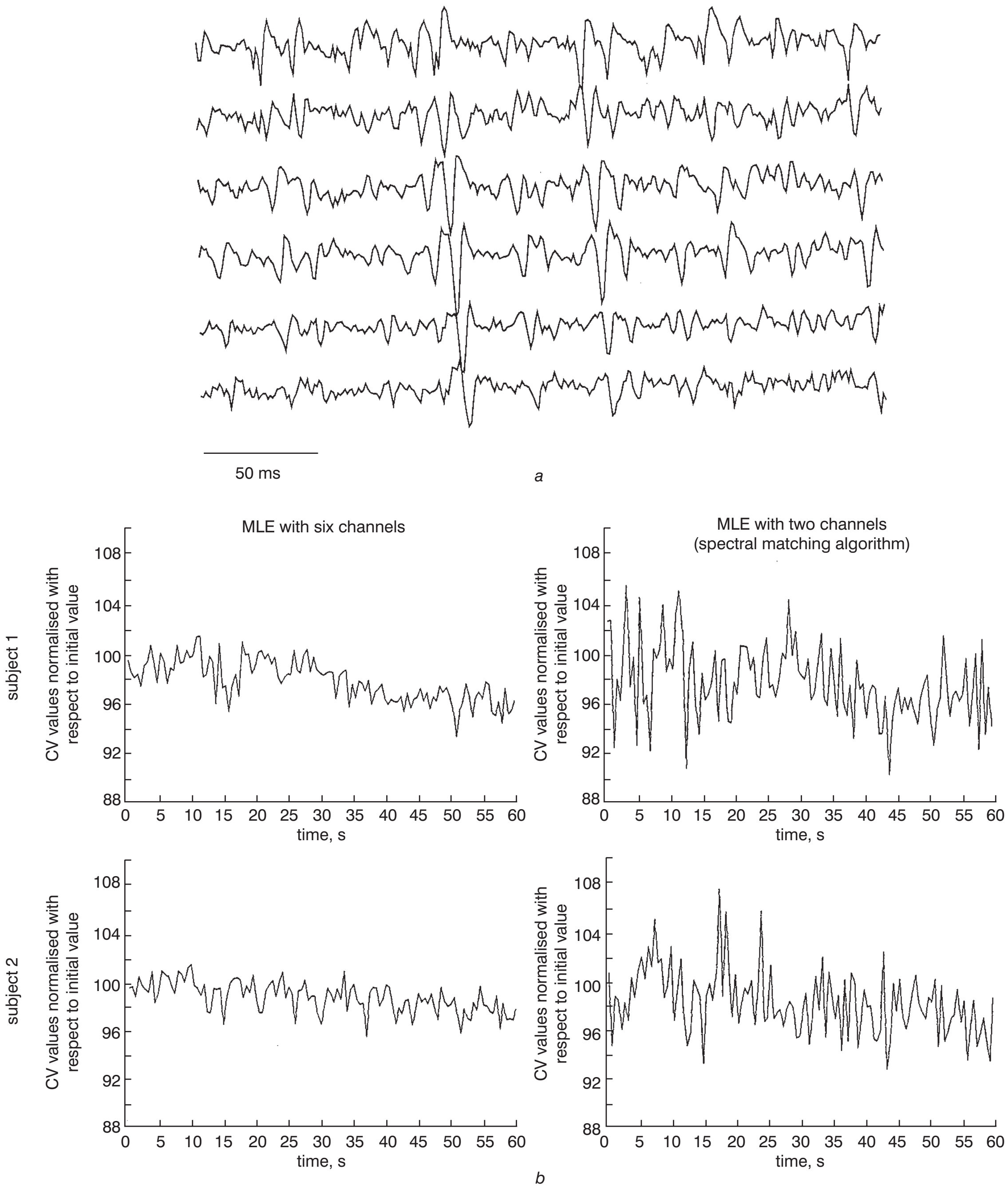

Fig. 13 *(a) EMG signals detected by linear electrode array from biceps brachii muscle during voluntary isometric contraction at 10% MVC, and (b) mean CV estimations (epoch length of 250 ms) computed during two contractions lasting 60 s at 10% MVC of two different subjects. MLE with iterative procedure is shown on left (using six channels), traditional two-channel estimations are shown on right (using central channels of six used for MLE). CV values are normalised with respect to intercept of regression line*

4 Discussion and conclusions

Mean muscle fibre CV estimated from the surface EMG signal is an important parameter for muscle fibre characterisation, fatigue monitoring and, in general, for the non-invasive assessment of muscles (MERLETTI *et al*., 1990). Nevertheless, surface techniques do not yet have a direct clinical application. This is mostly owing to the fact that traditional surface EMG processing techniques are affected by a number of uncontrollable factors that make the repeatability of the estimations quite poor (RAINOLDI *et al*., 1999). Mean CV estimation, for example, is biased in favour of the largest and most frequent MUAPs and is greatly affected by the muscle fibre CV distribution, the detection system, the inclination of the fibres with respect to the detection system, the position of the electrodes, the depth of the MUs, the electrode distance from the innervation zone and the tendon, the additive noise due to the electrodes and the electronic amplifiers, as well as to EMG activity far from the detection point. Subcutaneous layers and local tissue inhomogeneities seem to have a smaller influence on CV estimation. On the other hand, these factors play a very important role in detection selectivity and amplitude and frequency variable estimations (FARINA and RAINOLDI, 1999; SCHNEIDER *et al*., 1991). These effects can be investigated only using modern physical modelling techniques (FARINA and MERLETTI, 2001; MERLETTI *et al*., 1999*a*) that are based on precise description of the generation and detection of the surface EMG signal.

The separation of the different contributions to the surface EMG signal permits us to identify specific features of the individual MUs, for example their CVs, which reflects fibre size and type. The distribution of MU CV has been obtained in the past only with invasive, painful and time-consuming techniques (Troni *et al.*, 1983) and has been proven to provide important indications for the diagnosis of neuromuscular disorders (Stalberg *et al.*, 1996). Estimation of single MUAP CV from the surface EMG signal has practical relevance also in a number of other fields, such as ergonomics, geriatrics, sport and rehabilitation medicine, as shown, for example, by Merletti *et al.* (1999*d*).

Multichannel EMG detection provides additional information with respect to two-channel detection for MUAP extraction and classification, as we have shown in previous work (Farina *et al.*, 1998; Farina *et al.*, 2000; Gazzoni *et al.*, 2000; Merletti *et al.*, 1999*c*). In this paper, we focus on the estimation of the delay between signals, assuming that the extraction phase of the potentials is performed correctly. It has been shown that, using multichannel-based estimators, it is possible to improve considerably CV estimation compared with that involving traditional two-channel processing techniques. The variance of estimation can be substantially reduced with the proposed techniques, in the case of mean CV as well as in the case of single MUAP CV estimation, making it possible to distinguish between properties of different muscles and subjects and to improve CV distribution estimation with non-invasive techniques. Moreover, multichannel techniques are not significantly more affected by non-ideal factors (shape changes of the MUAP waveform along the array) than two-channel techniques. Finally, the availability of a fast algorithm for CV estimation permits us to reduce considerably the computation time compared with exhaustive searching.

The main conclusions of this paper are as follows:

- ML delay estimation can be viewed as the minimisation of the sum of mean square errors obtained when beamforming-based delay estimation is performed (eqn 5)
- in ideal conditions (infinite fibres aligned with the detection array), performances obtained with multichannel methods are better than those obtained by two-channel estimations with respect to bias and variance of the estimations (Fig. 6)
- the presence of local minima of the MSE function makes it necessary to introduce a coarse estimation of the delay before applying the iterative method (Fig. 4)
- the performance of multichannel algorithms with an iterative procedure for detecting the MSE minimum deteriorates if a large number of channels is selected (Fig. 5); this depends on the SNR, but a reasonable suggestion is to use six–seven channels
- in a complex medium, such as a layered volume conductor and anisotropic muscle, it is difficult to predict the change in shape and scale of the detected potentials owing to fibre inclination and the consequent bias in CV estimation. In the case of double differential recordings, CV bias can be either positive or negative (Fig. 7). For this reason, the statement that CV estimate should increase with the angle of inclination can be incorrect, as already outlined by Merletti *et al.* (1999*b*), and the criterion of minimum CV (Sadoyama *et al.*, 1985) may not be the best for electrode positioning
- the beamforming technique, with a proper selection of the reference signal, is less sensitive to fibre inclination than MLE (Figs 7 and 8), whereas the two techniques are almost equally affected by end-of-fibre and end-plate effects (Figs 9 and 10); the first technique is suggested for single MUAP CV estimation in the case of complex muscle anatomy (e.g. pennated muscles), whereas, in the case of parallel fibres, MLE should be preferred
- the low variance of CV estimates obtained with multichannel techniques allows identification of MUs on the basis of their CV, as shown in Fig. 12, and allows accurate tracking of the individual MU CV changes, possibly leading to MU type identification. Moreover, the availability of fast algorithms for CV estimation makes the proposed techniques applicable to real cases, when a very large number of MUAPs can be detected from an interference EMG signal.

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