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Cross-correlation between EMG and center of gravity during quiet stance: theory and simulations

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Abstract Several signal processing tools have been employed in the experimental study of the postural control system in humans. Among them, the cross-correlation function has been used to analyze the time relationship between signals such as the electromyogram and the horizontal projection of the center of gravity. The common finding is that the electromyogram precedes the biomechanical signal, a result that has been interpreted in different ways, for example, the existence of feedforward control or the preponderance of a velocity feedback. It is shown here, analytically and by simulation, that the cross-correlation function is depedent in a complicated way on system parameters and on noise spectra. Results similar to those found experimentally, e.g., electromyiogram preceding the biomechanical signal may be obtained in a postural control model without any feedforward control and without any velocity feedback. Therefore, correct interpretations of experimentally obtained cross-correlation functions may require additional information about the system. The results extend to other biomedical applications where two signals from a closed loop system are cross-correlated.

Keywords Cross-correlation · Closed loop · Postural control · Velocity feedback · Feedforward · Body sway

1 Introduction

A frequently asked question in studies of human postural control is whether a feedback control is sufficient to keep someone stabilized (Masani et al. 2003; Peterka 2003; Maurer and Peterka 2005) or if a feedforward control with predictive or adaptive dynamics is necessary (Fitzpatrick et al. 1996; Gatev et al. 1999; Morasso et al. 1999).

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The behavior of several variables associated with the postural control system during quiet stance may be associated with random processes and hence the tools used both in theoretical analyses and in experimental approaches have to be suited to analyze random signals. The cross-correlation between the electromyogram (EMG) of leg muscles and the horizontal projection of the center of gravity (COG) or the center of pressure (COP) has been used to infer features of the postural control system (Gatev et al. 1999; Masani et al. 2003). In both papers the cross-correlation indicated that the EMG preceded the COG and the COP, which were attributed either to a feedforward modulation of muscle activity that could predict the load pattern (Gatev et al. 1999) or to a feedback were velocity information is important (Masani et al. 2003). Masani et al. (2003) found cross-correlations similar to those of Gatev et al. (1999), which were also found in computer simulations of a posture control system based on velocity and position feedback. The cross-correlation of EMG and COG velocity (obtained by numerical differentiation) showed a significant negative peak at large negative time shifts (around -600 ms) and a smaller positive peak (most of the times non-significant). They report similar findings for the simulation studies. Their interpretations are that the velocity feedback provides a modulation of the muscle activity in an anticipatory manner and hence that a feedforward mechanism is not necessary.

In a recent paper the cross-correlation was used in a postural experiment to study the relations between the EMG and muscle length and also between muscle length and COG angle (Loram et al. 2005). In spite of using variables different from those in Gatev et al. (1999) and Masani et al. (2003), the basic conceptual issue is similar, which is the study of time relationships between two random signals in a closed loop postural control system.

Here, a linear systems analysis of a feedback model with stochastic inputs is developed which is relevant to studies in motor control (Fig. 1). The main tool in the analysis is the cross-correlation function between the EMG and the angle of the body with respect to earth-vertical (which is directly related to the COG) due to its previous uses in experiments

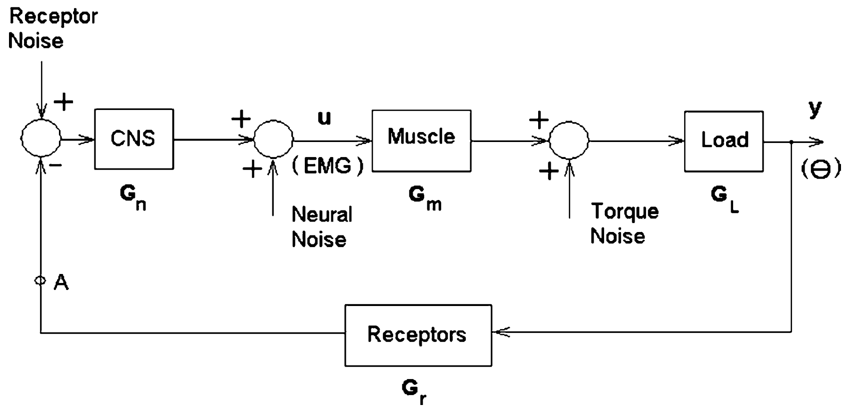

Fig. 1 Block diagram of a model of postural control for quiet stance

studying human postural control. Nevertheless, the analytical development will be both in the time and frequency domains. Hence G(ω), or simply G, denoting the frequency response function of any subsystem of the linear model will be used in the frequency domain analysis, and $g(t)$, the corresponding impulse response, will appear in the time domain description. The random signals will be described by auto- and cross-correlations in the time domain and by auto- and cross-spectra in the frequency domain.

2 The reference model

Figure 1 shows a basic model that represents parts of the postural control system in humans during quiet stance. It is similar to others described in the literature (Peterka 2000; Loram et al. 2001; Masani et al. 2003; Maurer and Peterka 2005). For mathematical tractability, all the subsystems are here assumed to be linear and time invariant, without any transport delays in the loop. The standing human, usually modeled by an inverted pendulum (Peterka 2000), is represented by the block Load, with frequency response G_{L}. The muscle spindle and other proprioceptive afferences (block Receptors) provide information about the angle Θ between the standing subject and the vertical direction with a corresponding frequency response G_{r}. The afferent inflow to the central nervous system (CNS) is actually the angle measurement plus a receptor noise. The CNS processes the afferent inflow with a frequency response G_{n}, generating an output which is corrupted by additive neural noise (e.g., due to synaptic bombardment of interneurons and motoneurons). In a very simplified view, this signal will be the command to the leg muscles that generate a torque with a frequency response G_{m}. Also, in a very simplified interpretation, this input command u to the muscles is approximated as the EMG that is recorded experimentally. Finally, there are torque perturbations, either internal or external, represented by the torque noise. All signals will be assumed to have zero mean, to simplify the expressions.

3 Open loop analysis

If we open the loop in the system of Fig. 1, for example at point A, the cross-correlation (C_{uy}) between the EMG, indicated as $u(t)$, and the angle Θ, indicated as $y(t)$, will be

$$C_{uy}(\tau) = E[u(t+\tau)y(t)] = g_m(-\tau) * g_L(-\tau) * C_{uu}(\tau) \quad (1)$$

where $E[.]$ is the expected value operator, $g_m(.)$ and $g_L(.)$ the impulse responses of the muscle and load subsystems, and $C_{uu}(.)$ the autocorrelation function of signal u. The torque noise and the EMG were supposed uncorrelated, which is reasonable in an open loop abstraction. The result in Eq. (1) says that the cross-correlation (**CCR**) between u and y is the convolution of the time-reversed impulse responses of the muscle and load blocks with the auto-correlation of the input signal u.

This result will be analyzed for two different cases:

(a) if the input signal u is white, then the cross-correlation between u and y will be the time-reversed version of the convolution between the impulse responses of two causal linear systems, and hence $C_{\mathrm{uy}}(\tau)$ will have values different from zero only for negative values of τ. In practice the zero values for positive τ would mean that they are statistically undifferentiated from zero. Therefore, in the hypothetical open loop situation, assuming for the moment that the load system G_{L} is not unstable, one would measure a CCR where the EMG would anticipate statistically the signal theta, without the need to postulate an "anticipatory" system driving the muscle.

(b) if the signal $u(t)$ is not white, then the CCR will be the convolution of the CCR that would be found in case (a) with the auto-correlation of the signal u. The resulting CCR would have nonzero values for positive and negative τ values but with the peaks due to $g_{\mathrm{m}}(t)$ and $g_{\mathrm{L}}(t)$ still occurring at negative time shifts.

4 Closed loop analysis

To avoid unnecessary mathematical manipulations, we simplify the control system to that of Fig. 2, which will suffice for

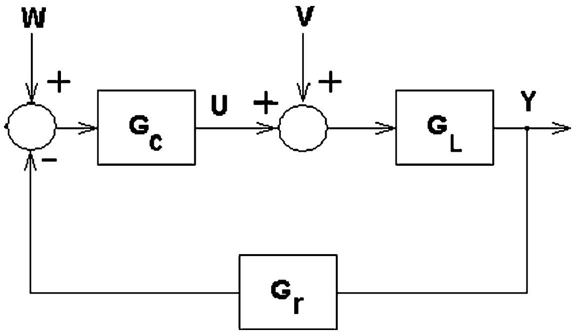

Fig. 2 Simplified block diagram, where W and V are uncorrelated noise sources with arbitrary power spectra. The measured input is U and the output is Y. The control, load and receptor frequency response functions are indicated by G_c, G_L and G_r, respectively

our purposes. The neural noise of Fig. 1 was merged with the receptor noise resulting in an equivalent noise process W. The derivations will be done in the frequency domain and, when appropriate, the auto- or cross-correlations will be obtained by Fourier anti-transformation. The noise sources $w(t)$ and $v(t)$ will be supposed independent (or at least uncorrelated). The signals in capital letters will indicate their frequency domain description. To be consistent with the cross-correlation definition in Eq. (1), the cross-power spectral density S_{uy} between random processes u and y will be taken as

$$S_{uy}(\omega) = \lim_{T\to\infty} \frac{1}{2T} E[U_T(\omega)Y_T^*(\omega)] \tag{2}$$

where

$$U_T(\omega) = \text{ Fourier Transform } [u_T(t)] \tag{3}$$

with

$$u_T(t) = \begin{cases} u(t) & -T < t < T \\ 0 & \text{elsewhere} \end{cases}$$

and similarly for signal y.

The analysis of the random signals in Fig. 2 will use finite Fourier transforms like in Eq. (3), and leave the expected value and limit operations as indicated in Eq. (2), for the final step. For simplicity of notation we shall omit the subscript T and the (ω), e.g., we shall use U instead of $U_{\mathrm{T}}(\omega)$.

From Fig. 2 we have the following equations:

$$Y = G_L V + G_L U \tag{4}$$

$$\begin{aligned} U &= -G_c G_r Y + G_c W \\ &= G_c W - G_c G_r G_L V - G_c G_r G_L U \end{aligned} \tag{5}$$

From (5) we can isolate U:

$$U = \frac{G_c W - G_c G_r G_L V}{1 + G_c G_r G_L} \tag{6}$$

Let us define $G_0 = G_c G_r G_L$. Multiplying Eq. (6) by U^* and taking expectation and then the limit as in Eq. (2), we have:

$$S_{uu}(\omega) = \frac{|G_c|^2 S_{ww}(\omega) + |G_0|^2 S_{vv}(\omega)}{|1 + G_0|^2} \tag{7}$$

Taking Y^* in Eq. (4), multiplying by U and taking expectations and the limit, we obtain:

$$S_{uy}(\omega) = G_L^* S_{uv}(\omega) + G_L^* S_{uu}(\omega) \tag{8}$$

Multiplying Eq. (6) by V^*, taking expectations and the limit, and using the fact that w and v are uncorrelated, one gets:

$$S_{uv}(\omega) = \frac{-G_0 S_{vv}(\omega)}{1 + G_0} \tag{9}$$

Substituting Eq. (9) into expression (8):

$$S_{uy}(\omega) = G_L^* S_{uu}(\omega) - \frac{G_L^* G_0 S_{vv}(\omega)}{1 + G_0} \tag{10}$$

In the open loop case, $G_0 = 0$ and hence

$$S_{uy}(\omega) = G_L^* S_{uu}(\omega) \tag{11}$$

which, gives

$$C_{uy}(\tau) = g_L(-\tau) * C_{uu}(\tau) \tag{12}$$

This expression is similar to that already presented when the model of Fig. 1 was analyzed in open loop. Again, the CCR between u and y will have peaks of the impulse response $g_L(t)$ appearing at negative values of τ.

We shall next obtain an expression for $S_{uy}(\omega)$ as a function only of the power spectra of the two noise sources v and w. Therefore, $S_{uu}(\omega)$ is eliminated from Eq. (10) by means of Eq. (7):

$$\begin{aligned} S_{uy}(\omega) = & \frac{G_L^* |G_c|^2 S_{ww}(\omega) + G_L^* |G_0|^2 S_{vv}(\omega)}{|1 + G_0|^2} \\ & - \frac{G_L^* G_0 S_{vv}(\omega)}{1 + G_0} \end{aligned} \tag{13}$$

which results in

$$S_{uy}(\omega) = \frac{G_L^* |G_c|^2 S_{ww}(\omega) - G_L^* G_0 S_{vv}(\omega)}{|1 + G_0|^2} \tag{14}$$

The expression above would be simpler to analyze if the denominator were unitary, so we shall define new noise sources w' and v' whose spectra are, $S_{ww}(\omega)/|1+G_o|^2$ and $S_{vv}(\omega)/|1+G_o|^2$ respectively. This means that the original noise processes would have their spectra altered by a linear system with frequency response $[1 + G_o]^{-1}$. With these definitions, expression (14) becomes:

$$S_{uy}(\omega) = G_L^* |G_c|^2 S_{w'w'}(\omega) - G_L^* G_0 S_{v'v'}(\omega) \tag{15}$$

From Eq. (15):

$$\begin{aligned} C_{uy}(\tau) = & g_L(-\tau) * g_c(\tau) * g_c(-\tau) * C_{w'w'}(\tau) \\ & - g_L(-\tau) * g_0(\tau) * C_{v'v'}(\tau) \end{aligned} \tag{16}$$

It should be noted that $g_c(\tau) * g_c(-\tau)$ is an even function of τ and so is its convolution with $C_{w'w'}(\tau)$. For a simpler interpretation of the result in Eq. (16), we shall assume that the noises w' and v' may be approximated by white noises with constant power spectra equal to 1, and that the feedback is unitary, $G_r = 1$. Then, $G_o = G_c G_L$ and from Eq. (15) one gets

$$S_{uy}(\omega) = G_L^* |G_c|^2 - G_c |G_L|^2 \tag{17}$$

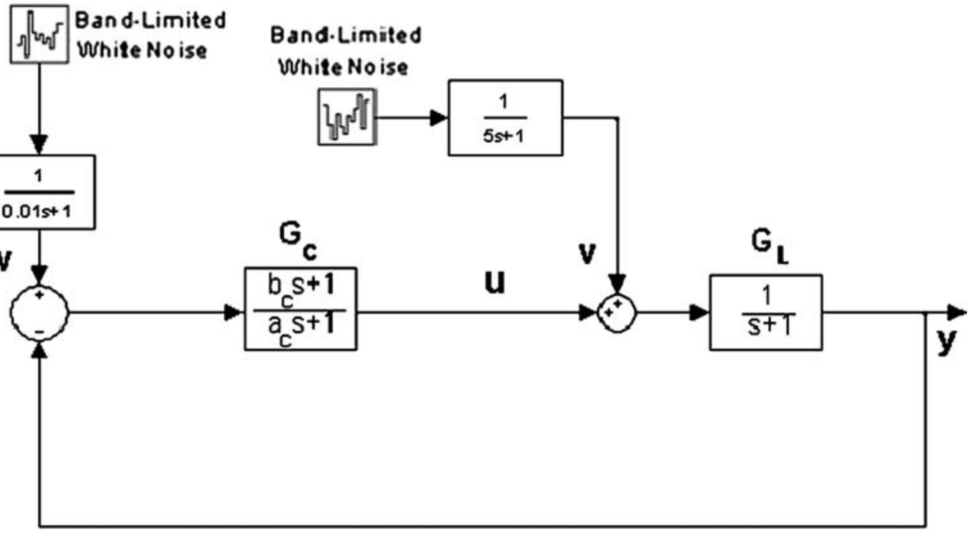

Fig. 3 Block diagram of simulated system, where different transfer functions were used for G_c by choosing different values for a_c and b_c, as described in the text. Noise signal W had a wide band spectrum but V had a spectrum more concentrated in the low frequencies

and from (17), by anti-transformation:

$$C_{uy}(\tau) = g_L(-\tau) * C_{cc}(\tau) - g_c(\tau) * C_{LL}(\tau) \quad (18)$$

where $C_{cc}(\tau) = g_c(-\tau) * g_c(\tau)$ and $C_{LL}(\tau) = g_L(-\tau) * g_L(\tau)$ are even functions of τ. Expression (18) shows that the first term will give a positive peak of $C_{uy}(\tau)$ at a negative time shift value and the second term a negative peak at a positive time shift, both due to causality of each block in Fig. 2. Loosening the restriction of white w' and v' the first term in Eq. (18) would be smoothed by a convolution with $C_{w'w'}(\tau)$ and the second term by a convolution with $C_{v'v'}(\tau)$, as evidenced by expression (16).

Therefore, the CCR between signals u and y, or between the EMG and angle theta in the postural control model, would typically have a peak at negative time shifts, irrespective of the existence of a velocity feedback, or an "anticipatory" feedforward pathway, or still, a predictive or adaptive feedback system. More complex cases may arise for different system and noise parameters, as will be explored by simulations of a basic model.

5 Simulations

For illustration purposes, some simulation results will be presented of the model in Fig. 2. The model was implemented in Simulink (Matlab, Mathworks) as shown in Fig. 3, where G_r in Fig. 2 was taken as unitary. The noise signals w and v were not white in order to represent better the biological reality. The subsystems G_c and G_L were assumed first order to simplify matters.

As far as our knowledge of the literature goes, the power spectra of the noises w and v have not yet been estimated from experimental data, so we assumed two different spectra for the receptor/neural noise w with time constants 0.01 and 0.1 s and a spectrum for the torque noise v with a time constant of 5 s. For comparison, noise sources equivalent to w and v in the literature on postural control simulations have been used with widely different time constants, e.g. 100 s in Maurer and Peterka (2005) for $w(t)$ and 0.5 s in Loram et al. (2001) and 1 s in Masani et al. (2003) for $v(t)$.

The first subsystem in Fig. 3, G_c, would represent a neural controller composed of a proportional and a derivative term (if $b_c \neq 0$) but without the unlimited gain increase at high frequencies due to the denominator $a_c s + 1$. The load, which in practice would be typically a second order system with phase lag (Masani et al. 2003; Maurer and Peterka 2005), was approximated by a first order system with phase lag, G_L, which will not cause qualitative changes in the cross-correlation analysis. One could still question if the parameters used were within a biologically acceptable range for a postural control system. In simulations of such a system, various investigators (Loram et al. 2001; Masani et al. 2003; Maurer and Peterka 2005) have used roughly similar values of the moment of inertia, product mgh (mass x acceleration due to gravity x height of the center of mass), the proportional gain Kp and the derivative gain Kd. Representative values were adopted as follows: I=66 kg/m^2, mgh=650 kgm^2/s^2, Kp=1150 Nm/rad and Kd=250 Nms/rad. With these values, and assuming zero transport delays in the loop of the models in (Masani et al. 2003; Maurer and Peterka 2005), the closed loop zero was at -4.60 and the closed loop poles were at $-1.89 \pm j2.00$. When in the simulated system of Fig. 3 the parameter values were $a_c = 2$ and $b_c = 0$, the closed loop poles were $-0.75 \pm j0.66$ and there was no zero. With $a_c = 0.2$ and $b_c = 0$, the closed loop poles were $-3.00 \pm j1.00$ and there was no zero and finally, with $a_c = 0.2$ and $b_c = 1$, the closed loop poles were -1.00 and -10.00 and the zero was -1. Therefore, the simulated system had poles and zeros within an order of magnitude of those used in previous work in the literature.

The system in Fig. 3 was simulated for different parameter values a_c and b_c, as shall be specified in the text below and for two different filters to generate the random signal w: one with denominator $0.01s + 1$, as shown in Fig. 3, and the other with denominator $0.1s + 1$. The simulations were run with the following features: final time 250 s, fixed time step 1 ms, fifth order Dormand and Prince numerical integration method. The normalized and unbiased cross-covariance function between the two resulting random signals u and y was computed. To avoid transients in the random signals due to the zero initial conditions in the simulated system, the first 50 s of simulated signal samples were discarded.

In the first simulation the parameter values for G_c were $b_c = 0, a_c = 0.2$. The CCR between u and y (Fig. 4a) had a 0.56 positive peak at a time shift −0.25 s and a −0.20 negative peak at a time shift of 0.45 s. Next, for $b_c = 0, a_c = 2$, the CCR between u and y had a positive peak of amplitude 0.60 (Fig. 4b) at a time shift −0.55 s and a diffuse negative peak (amplitude −0.20) at positive time shifts. This displacement of the positive peak of the CCR to more negative time shift values can be explained by taking Eq. (18) as a rough approximation. When making $a_c = 2$, the impulse response $g_c(\tau)$ was much slower and hence the function $C_{cc}(\tau) = g_c(-\tau) * g_c(\tau)$ was more spread out around abscissa 0. This lead to a much slower waveform in the contribution of $g_L(-\tau)*C_{cc}(\tau)$ to $C_{uy}(\tau)$ at negative time shifts, making the peak occur at a more negative abscissa. In a third simulation, $b_c = 1, a_c = 0.2$, which can be compared also to the situation of the first simulation. Now the CCR (Fig. 4c) was more symmetrical and more concentrated near the origin. The positive peak occurred at a time shift around −0.025 s, which is an order of magnitude smaller than when the block G_c only had a pole. The inclusion of a zero increased the phase advance caused by block G_c, which should increase the phase advance of $S_{uy}(\omega)$ (see Eq. (15) or (17)). By the Fourier theory, a phase advance in the cross-spectrum should cause a decrease in time shifts of peaks in the cross-correlation, besides potential changes in shape. The fourth simulation had the purpose of indicating the influence of the noise power spectrum on the position of a CCR peak. Using the same parameters as in Fig. 4c, $b_c = 1, a_c = 0.2$, instead of using a filter with denominator $0.01s + 1$ to generate w, as in Fig. 3, this simulation employed a filter with denominator $0.1s+1$, i.e., the noise w had less power at high frequencies. The CCR (Fig. 4d) had a 0.43 positive peak occurring at time shift −0.1 s and a −0.3 negative peak occurring at time shift 0.1 s. A narrower power spectrum for noise w will result in a wider $C_{ww}(\tau)$, which from Eqs. (14) and (16) will wider $C_{uy}(\tau)$, as the simulations have shown in going from Fig. 4c to d.

In the next set of simulations, the system parameters were kept constant, with $b_c = 1$ and $a_c = 0.2$. The noise power spectra were changed, one at a time. In Fig. 5a, noise w was generated by filter $1/(0.1s+1)$ and noise v by filter $5/(0.5s+1)$. This means that the simulated system is similar to that of Fig. 4d but with an increased power of the noise v. The change in the cross-correlation is substantial, as now, with the higher influence of the noise v (torque noise) the dominant peak in the CCR is a negative peak at positive time shifts, in accordance with expressions (14) and (16). In Fig. 5b the noise power of w (receptor/neural noise) was decreased in comparison with Fig. 5a by filtering with $0.2/(0.1s + 1)$, the effect being a left shift of the negative (and dominant) peak of the CCR. In the next case, the CCR in Fig. 5c did not change much from the previous case, even though, here, the noise w was filtered by $2/(s + 1)$, which means that the plateau power value increased but the bandwidth decreased. A noticeable difference in the CCR is a small notch near time lag 0. Keeping the power spectrum of w but reducing the power in v by using the filter $1/(0.5s + 1)$ caused a dramatic change in the CCR as seen in Fig. 5d. In this case there is a large positive peak at negative time lag with an abrupt fall near $\tau = 0$ and a slow fall for negative time lags.

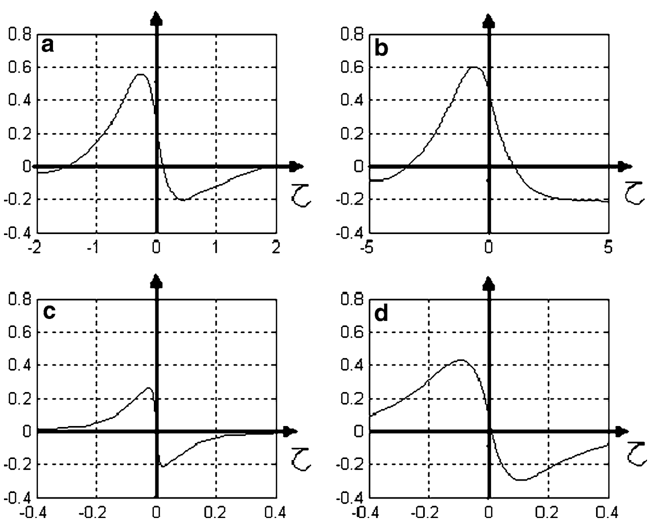

Fig. 4 Cross-correlation functions for different simulation parameters. **a** $b_c = 0, a_c = 0.2$, **b** $b_c = 0, a_c = 2$; **c** $b_c = 1, a_c = 0.2$; **d** $b_c = 1, a_c = 0.2$. Simulation results in **a**, **b**, and **c** used the noise filters shown in Fig. 3, while in **d** the filter to produce w was $1/(0.1s + 1)$. As the random signals have zero mean the functions above are also the cross-covariance functions

6 Discussion

The results presented in this work rely on a linear system approximation to the postural control system of a standing human. Actually, the results and conclusions are much more general, as they apply for any closed loop system which can be approximated by a linear system. The first part of the text gave analytical expressions for the cross-correlation and cross-spectrum between two signals u and y (Fig. 2) that are counterparts of the EMG and the angle between the standing subject and earth-vertical in the simple postural control system model. The second part presented simulations that corroborated and extended the theoretical predictions of the first part. Basically, the theory shows that the main peak in the CCR may happen at negative time lags, independent of the existence of derivative neural control or predictive or

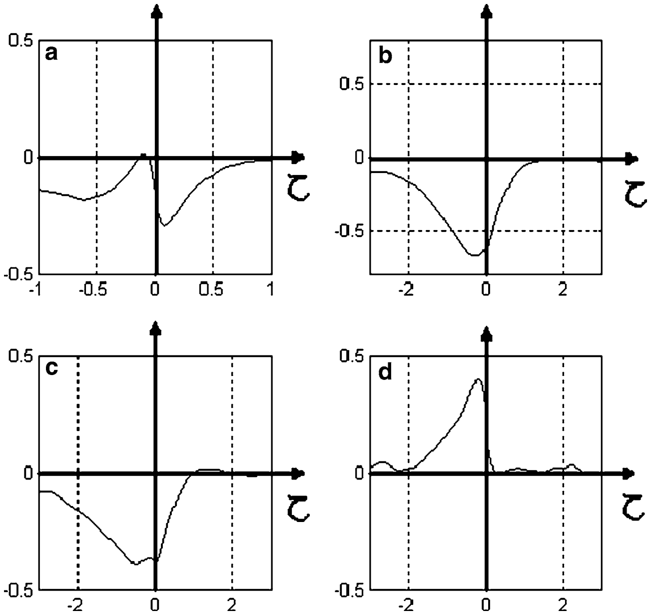

Fig. 5 Cross-correlation functions for different noise parameters. In all cases the system parameters were the same, with $a_c = 0.2$ and $b_c = 1$. For (**a**), (**b**), and (**c**) the filter that generates v was $5/(0.5s+1)$ and in (**d**) it was $1/(0.5s+1)$. In (**a**) the filter that generates w was $1/(0.1s+1)$, in (**b**) it was $0.2/(0.1s+1)$, and in (**c**) and (**d**) it was $2/(s+1)$. Very different cross-covariances can be obtained for the same system, if the noise properties vary

feedforward postural control. The simulations suggested that relatively small changes either in system parameters or noise characteristics may shift the peaks in the CCR by considerable amounts (Figs. 4 and 5). These findings do not prove that there is no feedforward or velocity-dependent feedback acting in the human postural control system. They may indeed be present (Jeka et al. 2004), but the issue is that their presence or their importance cannot be assessed by the cross-correlation between the EMG and Θ (or the COG or COP).

Therefore, in studies of the postural control system, or, in fact, of any closed loop system, the peak positions in the CCR should be interpreted with special care. If possible, external input signals should be applied to the system in an effort to study specific subsystems as done very elegantly in (Fitzpatrick et al. 1996). This additional information on specific subsystems may allow an appropriate interpretation of experimental cross-correlation functions because many terms in Eq. (16) will be known (estimated experimentally). Alternatively, the experimental cross-correlation could be incompatible with Eq. (16), derived from the models in Fig. 1 or 2. This would then point to the need for a more refined model and lead to new advances.

Will the results of this paper be valid in view of the many simplifications that were adopted? The linear approximation of the postural control system seems reasonable for quiet stance (Peterka 2002). The simplification of simulating a unitary feedback system has been often adopted in the literature (Peterka 2000; Masani et al. 2003; Maurer and Peterka 2005) because it helps in the interpretation and it should not have induced qualitative changes in the results. The inclusion of the propagation delays through the afferent and efferent pathways (see Fig. 2) could be achieved by multiplying G_r by $e^{-j\omega T_a}$ and G_c by $e^{-j\omega T_e}$, where T_a and T_e would represent the delays in the afferent loop and in the central nervous system plus the efferent pathway. In expressions (15) and (16) there would be changes in the negative terms associated with the blocks G_c and G_r with some complications in the interpretations. Again, these added complexities should not qualitatively change the general results.

A recent paper (van der Kooij et al. 2005) analyzed a closed loop model of postural control and showed that the system identification based on $S_{uy}(\omega)/S_{uu}(\omega)$ may lead to poor results, where u and y could be associated with the EMG and Θ or other variables in the closed loop control model. No expression was derived for the cross-correlation function $C_{uy}(\tau)$. On the other hand, the derivations of the present paper dissect the dependence of the cross-correlation function on the system and the noise characteristics of the postural control system. The theory and simulations reported here showed that even a velocity dependent feedback is not required to explain the experimental findings of previous authors (Gatev et al. 1999; Masani et al. 2003), contradicting current views (Masani et al. 2003; van der Kooij et al. 2005).

7 Conclusion

Within the context of studies of posture control, the location of the main peak of the CCR between EMG and COG (or other signals) during quiet stance is dependent on many factors that include both the system parameters and the characteristics of the stochastic input signals. Due to this complexity, the interpretation of the experimentally obtained CCRs as to the type of motor control – feedback without velocity component, feedback with velocity component, feedforward with open loop, feedforward with close loop, etc – may require complementary information. The conceptual conclusions reached in this paper are valid for other biomedical applications where two signals measured from a closed loop system are cross-correlated.

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References

Fitzpatrick R, Burke D, Gandevia SC (1996) Loop gain of reflexes controlling human standing measured with the use of postural and vestibular disturbances. J Neurophysiol 76:3994–4008

Gatev P, Thomas S, Kepple T, Hallett M (1999) Feedforward ankle strategy of balance during quiet stance in adults. J Physiol 514:915–928

Jeka J, Kiemel T, Creath R, Horak F, Peterka R (2004) Controlling human upright posture: velocity information is more accurate than position or acceleration. J Neurophysiol 92:2368–2379

Loram ID, Kelly SM, Lakie M (2001) Human balancing of an inverted pendulum: is sway size controlled by ankle impedance? J Physiol 532:879–891

Loram ID, Maganaris CN, Lakie M (2005) Active, non-spring-like muscle movements in human postural sway: how might paradoxical changes in muscle length be produced? J Physiol 564.1:281–293

Masani K, Popovic MR, Nakazawa K, Kouzaki M, Nozaki D (2003) Importance of body sway velocity information in controlling ankle extensor activities during quiet stance. J Neurophysiol 90:3774–3782

Maurer C, Peterka RJ (2005) A new interpretation of spontaneous sway measures based on a simple model of human postural control. J Neurophysiol 93:189–200

Morasso PG, Baratto L, Capra R, Spada G (1999) Internal models in the control of posture. Neural Netw 12:1173–1180

Peterka RJ (2000) Postural control model interpretation of stabilogram diffusion analysis. Biol Cybern 82:335–343

Peterka RJ (2002) Sensorimotor integration in human postural control. J Neurophysiol 88:1097–1118

Peterka RJ (2003) Simplifying the complexities of maintaining balance. IEEE Eng Med Biol Mag 22:63–68

van der Kooij H, van Asseldonk E, van der Helm FCT (2005) Comparison of different methods to identify and quantify balance control. J Neurosci Methods 145:175–203