Age-related changes in inter-joint coordination during walking

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Innovative Methodology

Age-related changes in inter-joint coordination during walking. J Appl Physiol 117: 189–198, 2014. First published May 22, 2014; doi:10.1152/japplphysiol.00212.2014.—Existing methods to assess inter-joint coordination in human walking have several important weaknesses. These methods are unable to define instantaneous changes in coordination within the stride cycle, 2) coordination between multiple joints, or 3) the coupling strength of joint rotations rather than their phase relationships. The present paper introduces a new method called generalized wavelet coherence analysis (GWCA) that solves these three fundamental limitations of previous methods. GWCA combines wavelet coherence analysis with a matrix correlation method to define instantaneous correlation coefficients as the coupling strength for an arbitrary number of joint rotations.

The main purpose of the present study is to develop GWCA to quantify inter-joint coordination and thereby assess age-related differences in the coordination of human gaits. Nine young and 19 healthy older persons walked 5 min on a treadmill at three different gait speeds. Joint rotations of the lower extremities were assessed by a Vicon three-dimensional motion capture system. The main results indicated that the older group had significant weaker correlations (t-tests: \( P < 0.0001 \)) in the preswing phase compared with the younger group for all gait speeds. The age-related differences in inter-joint coordination were more pronounced than the age-related differences in rotations of the individual joints. The intra-stride changes in inter-joint coordination were in agreement with recent findings of intra-stride modulations in neural activity in the sensorimotor cortex. Thus change in the inter-joint coordination assessed by GWCA might be an early indicator of functional decline.

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TEMPORAL PATTERNING IN PHYSIOLOGICAL SYSTEM has been investigated from coordination of human movements to the patterns of muscle activations and synchronization of ensembles of neurons (1, 4, 11). Biological rhythms are rarely perfectly synchronized across multiple spatial and temporal scales but instead fluctuate in complex coupling-decoupling patterns (11). These coupling-decoupling patterns enable the biological rhythms to emerge and adapt according to changing internal and contextual circumstances and, consequently, provide plasticity in the functioning of physiological systems. Most signals from these physiological systems, such as the measurement of kinematics of the movement system, electromyogram (EMG) from the muscular system, and electroencephalogram (EEG) of human cortex, therefore fluctuate in a complex and nonharmonic manner because of changes in the coordination of a large number of system components (37, 38).

One of the main fields to investigate the coordination of biological rhythms is the inter-joint coordination of rhythmical movements such as human gait. Gait function generally declines with increasing age, yielding alterations in several measures of the walking pattern of older persons. Aging is accompanied by a decline in gait speed, a shortening of step length, an increase in cadence, and a relatively longer duration of the double support phase compared with the single support phase (i.e., shortened swing time) (3, 10, 14, 25, 50). Furthermore, older persons have a longer step time variability and larger step length and step width variability compared with younger persons (50). Aging of the neuromuscular system is related to changes in both the gait kinematics and kinetics. Older persons often have a reduced hip extension in the loading response phase and reduced plantar flexion at the push-off at the preswing phase (23, 24). These alterations in gait kinematics are reflected in a decline in the push-off moment and power of older persons, as indicated by a decrease in ankle plantarflexion moment and power in the preswing phase, an increase in hip extension moment and power in the loading response phase, and an increase in hip flexion moment in the early swing phase (9, 19, 24, 31, 32, 41, 50). These combined age-related changes in gait kinematics and kinetics are assumed to reflect changes in inter-joint coordination due to degeneration of the neuromuscular system (26). Thus age-related alteration in the inter-joint coordination of gait is an important factor to explain the decline in gait function and associated higher risk of falling observed in older persons.

Many techniques have been developed to quantify inter-joint coordination in human movement, including cross-correlations, spectral coherence analysis, and phase synchronization (8, 26, 34, 42, 49, 53). However, these conventional methods have at least one of three fundamental limitations. First, several of the methods compute a single parameter that is by definition unable to assess the temporal change in the inter-joint coordination within the stride cycle. Second, the methods quantify the coordination between only two joint rotations at the time, whereas human gait involves multiple joint rotations. Third, the methods identify the relative phase between joint rotations rather than their coupling strength. The present study solves these three fundamental limitations by developing generalized wavelet coherence analysis (GWCA). This method computes the instantaneous correlation coefficient as the coupling strength for an arbitrary number of joint rotations. Wavelet coherence analysis has been applied to a wide range of physiological signals during the last decade, such as accelerometry (21), EEG (28), EMG (46), electrocardiograms (22, 47), blood oxygenation level (33), temperature, respiration and heart rate variability (30, 35), functional near infrared spectroscopy (15), cerebral blood flow (36), inter-cranial pressure (27), and blood pressure (23). However, wavelet coherence analysis has, to the authors’ knowledge, not been combined with a correlation matrix method to investigate the instantaneous correlation of more than two physiological signals. Thus the main aim of the present study is to develop GWCA to quantify inter-joint coordination and thereby assess age-related differences in the inter-joint coordination of human gait.

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Glossary

\[ R(s) \] scale-dependent instantaneous correlation coefficient computed by GWCA

\[ R_t \] mean of \( R(s) \) across the scales of the lower 75th percentile for each time instant \( t \)

\[ R_{\text{max}} \] intra-stride maximum of median \( R_t \)

\[ R_{\text{min}} \] intra-stride minimum of median \( R_t \)

MATERIALS AND METHODS

Nine younger and 19 older healthy adults participated in the present study (see Table 1 for sample characteristics). The study was approved by the regional ethical committee and all subjects signed a written consent before participating.

Walking tests were performed on a motorized treadmill (Woodway, Waukesha, WI). To acclimatize to the test situation, participants first walked 10–15 min on the treadmill at a comfortable speed. Testing consisted of 5 min walking trials at three different walking speeds (preferred speed, –20%, and +20% of preferred speed). The order of the trials was randomized for each participant. The preferred walking speed was estimated at the end of the acclimatization period (17). Gait kinematics were measured at 100 Hz by a Vicon three-dimensional (3D) motion capture system with 10 cameras (Vicon Motion Systems Ltd, Oxford, UK). Camera residuals were below 0.5 mm for all trials. Sixteen 14-mm infrared retroreflective markers were placed on bony landmarks on the lower extremities according to the conventional gait model (20). The markers were placed by a certified prosthetist orthotist with 9 years experience with marker placement for the conventional gait model. A Woltering low-pass filter was employed with the kinematic data to filter out the high-frequency marker movements with amplitudes below 3 mm (52). These movements were marker vibrations after heel strikes due to the motion of the skin relative to the bony landmarks and were confirmed by a visual residual check of the low-pass filtering. The 3D joint angles were estimated according to the Euler joint convention for the ankle, knee, and hip joints together with the foot inclination and pelvic rotation (20). A total of 15 joint angle series was assessed for each leg to describe the gait kinematics of the lower extremities.

Generalized wavelet coherence analysis. GWCA is developed as a combination of 1) a wavelet coherence analysis to assess the intra-stride change in the inter-joint coordination and 2) a correlation matrix method to assess the inter-joint coordination of multiple joints. Below, I provide a nontechnical description of GWCA and how it is employed to a set of 15 joint angle series. Additional technical details of GWCA can be found in the Appendix.

Conventional coherence analysis is based on a Fourier decomposition of the joint angle series into a set of oscillations where the wavelength (i.e., scale) of each oscillation is equal to its inverse frequency (51). Coherence analysis determines a correlation coefficient that numerically defines the coupling strength between the oscillations of two joint angle series. Thus coherence analysis makes it possible to decompose the coordination of two joint angle series into intra-stride coordination (i.e., small wavelengths or time scales) and inter-stride coordination (i.e., large wavelengths or time scales). Conventional coherence analysis assumes that the amplitudes and phase relationships of the oscillations of the joint angle series do not change in time such that the correlation coefficient for each oscillation is time independent (51). However, joint rotations couple and decouple within each stride and, consequently, the intra-stride change of their coordination (i.e., coupling strength) has to be assessed by an instantaneous correlation coefficient. Wavelet coherence analysis addresses the shortcomings of conventional coherence analysis by decomposing the joint angle series into a set of time-dependent waveforms (i.e., a wavelet transformation; see Fig. 1A). Both the time-dependent amplitude and phase of the waveforms enable wavelet coherence analysis to detect the instantaneous coordination between two joint angle series (12, 48). The instantaneous coordination is defined by a series of instantaneous correlation coefficients for each wavelength (i.e., scale). The present study focuses on the intra-stride change in the instantaneous correlation coefficients for time scales ranging from 1/20 to 1/2 of the mean stride time (see Fig. 1B). The correlation coefficients for time scales below 1/20 of the mean stride time correspond to low-amplitude noise and are not considered in later GWCA.

The set of 15 joint angle series provides a total of \( 15 \times 15 = 225 \) joint angle pairs for the wavelet coherence analysis. Thus the inter-joint coordination is defined by 225 series of instantaneous correlation coefficients for each time scale. The correlation matrix method computes a single instantaneous correlation coefficient across all joint angle series by reducing the \( 15 \times 15 \) correlation matrix into set of 15 eigenvalues (40). Each of the eigenvalues reflects the coordination of each joint angle series to the other 14 joint angle series. The correlation matrix method then transforms the maximum eigenvalue \( \lambda_{\text{max}}(s) \) to the general instantaneous correlation coefficient \( R(s) \) for each time scale \( s \) by the following equation (40):

\[
R(s) = \frac{1}{m-1} \left[ \lambda_{\text{max}}(s) - 1 \right]
\]

where \( m = 15 \) is the number of joint angle series. This transformation does not apply to the other eigenvalues (40), but the temporal change in the maximum eigenvalue \( \lambda_{\text{max}}(s) \) is closely related to the temporal change of the other 14 eigenvalues. Thus \( R(s) \) defines the overall coordination of the 15 joint angle series (see Fig. 1C). In all sets of joint angle series, \( R(s) \) becomes constant within the entire stride cycle for time scales above 1/5 of the mean stride cycle duration. Thus only \( R(s) \) values for time scales between 1/20 and 1/5 of the mean stride time are considered in the definition below of the intra-stride change in the inter-joint coordination.

Intra-stride change in the inter-joint coordination. In gait analysis, intra-stride changes of joint angles are typically normalized to the stride time (i.e., 0–100% of stride cycle) and represented as a mean or median value computed across all strides. The following procedure creates a similar representation of the intra-stride change in the general instantaneous correlation coefficient, \( R(s) \). First, the mean \( R \) of \( R(s) \) is computed across the lower 75th percentile of the \( R(s) \) [i.e., the lower 75% of area below the \( R(s) \) curve at time instant \( t \)]. The lower 75th percentile of \( R(s) \) is used to consider potential variation in the scale dependency of \( R(s) \) at each time instant \( t \), but the present results were not sensitive to the choice of percentile and no age or gait speed differences was found for the percentile values. The computation of the mean \( R \) of \( R(s) \) is also justified by the absence of both age and gait speed differences in the scale dependency of \( R(s) \). Second, \( R \) of each leg is divided into sections between consecutive heel strikes and normalized to stride time (see the ensemble of black lines in Fig. 1D). The heel strikes and toe offs are identified to isolate the single and double support phases within the stride cycle. The heel strikes are identified as the intra-stride maximum of the heel marker in the anterior-posterior direction; the toe off is identified as the intra-stride minimum of the toe marker in the anterior-posterior direction. This

<table>
<thead>
<tr>
<th>Young Group</th>
<th>Old Group</th>
<th>( P ) Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sex, male/female</td>
<td>5/4</td>
<td>6/14</td>
</tr>
<tr>
<td>Age, yr</td>
<td>31.7 (5.2)</td>
<td>80.5 (6.5)</td>
</tr>
<tr>
<td>Height, cm</td>
<td>172.9 (10.1)</td>
<td>163.5 (7.5)</td>
</tr>
<tr>
<td>Body mass, kg</td>
<td>75.6 (17.9)</td>
<td>70.4 (10.1)</td>
</tr>
<tr>
<td>Pref. gait speed, m/s</td>
<td>1.11 (0.11)</td>
<td>1.05 (0.10)</td>
</tr>
</tbody>
</table>

Values are means ± SD. Note that the \( P \) values are given for independent-sample \( t \)-tests between the groups of older and younger persons.
identification is within 10-ms deviation (i.e., 1 sample) from the method proposed by Hreljac and Marshall (16). Third, the median \( R_t \) is computed across the normalized sections of \( R_t \) (see the red line in Fig. 1D). There is no significant difference in median \( R_t \) between the left and right leg, and median \( R_t \) is therefore computed across the normalized \( R_t \) sections of both legs.

The median \( R_t \) has two distinct maxima and two distinct minima within the stride cycle; one maximum, \( R_{\text{max}} \), within each of the double support phases (i.e., loading response and the preswing phase) and one minimum, \( R_{\text{min}} \), within each of the single support phases (i.e., stance and swing phase) (see Fig. 1D). \( R_{\text{max}} \) represents the points in the stride cycle with the strongest inter-joint coordination; \( R_{\text{min}} \) represents the points in the stride cycle with the weakest inter-joint coordination.

Statistics. Age and speed effects on \( R_{\text{max}} \) and \( R_{\text{min}} \) were assessed by an unbalanced two-way ANOVA with post hoc pair-wise comparison using \( t \)-tests. The significance level of the independent sample \( t \)-tests was set at \( P = 0.004 \) according to the Bonferroni correction for 12 pair-wise comparisons (4 intra-stride \( R_{\text{max}} \) and \( R_{\text{min}} \) multiplied by 3 speed conditions). The intra-stride asymmetry in \( R_t \) was assessed as the difference between \( R_{\text{max}} \) of the double support phases (i.e., loading response vs. preswing phase) and the difference between \( R_{\text{max}} \) of the single support phase (i.e., stance vs. swing phase). The intra-stride asymmetry was tested by paired sample \( t \)-tests for both the young and the older group for each gait speed condition.

RESULTS

Figure 2 shows representative examples of median \( R_t(s) \) across the common minimum of strides (i.e., 200 strides) over the course of 5 min of walking for a young person (Fig. 2A) and an old person (Fig. 2B). Both contour plots indicate that median \( R_t(s) \) shifted between strong and weak inter-joint coordination with respect to the transitions between single and double support phases. The local maximum of median \( R_t(s) \) of the preswing phase was larger for the young person across multiple temporal scales compared with the older person (compare the contours plots in Fig. 2, A and B).

All median \( R_t \) for both the younger and healthy older persons and for all speed conditions had a characteristic shape dependent on the transitions between single and double support phases (see Fig. 3). The inter-joint coordination declined toward the least coordinated point, \( R_{\text{min}} \), at the end of the stance phase and in the middle of the swing phase. After \( R_{\text{min}} \), inter-joint coordination increased toward \( R_{\text{max}} \) in the middle of both the loading response and the preswing phases. An asymmetry in median \( R_t \) was present for the younger persons, indicated by a significant difference between the two \( R_{\text{max}} \) \( t \)-tests: all \( P < 0.005 \) and the two \( R_{\text{min}} \) \( t \)-tests: \( P < 0.005 \). No significant asymmetry in \( R_t \) was observed for the healthy older group. A two-way ANOVA indicated a significant smaller \( R_{\text{max}} \) in the healthy older group compared with the younger group (see Table 2). Furthermore, \( R_{\text{min}} \) was significantly larger in the healthy older group in the stance phase, but no significant differences were present in the swing phase (see Table 2). However, the post hoc \( t \)-tests indicated that only the \( R_{\text{max}} \) in the preswing phase had significant age-related differences (see Fig. 3, top). The larger \( R_{\text{max}} \) for the younger group in the loading response phase was highly significant, and in the fast gait speed condition all \( R_{\text{max}} \) values of the younger group were larger than the \( R_{\text{max}} \) values of the healthy older group (see Fig. 4C). The difference in inter-joint coordination between the young and older persons was more pronounced compared with differences in individual joint kinematics illustrated by hip joint flexion/extension and plantar/dorsiflexion (see Fig. 4, A and B, respectively). A two-way ANOVA indicated no significant effects of gait speed on either \( R_{\text{max}} \) or \( R_{\text{min}} \).

DISCUSSION

The main purpose of the present study was to develop GWCA to quantify inter-joint coordination and thereby assess age-related differences in the coordination of human gaits. The GWCA indicated a decline in inter-joint coordination of older persons in the preswing phase. The intra-stride change in inter-joint coordination is in accordance with the intra-stride change in the phase coupling between joint rotations found in previous studies (2, 26). One of these studies also found significant age-related differences in the phase coupling of the shank and the thigh segment in the double support phase (2). However, previous studies assessed the relative phase, and not strength, of the coupling of two segments only. GWCA assesses the coupling strength of an arbitrary number of joints and, thus, provides a more general assessment of inter-joint coordination compared with previous methods.

The phase-dependent difference in the inter-joint coordination is related to changes in joint kinematics reported in the literature. Kerrigan et al. (24) reported a speed-independent increase in hip extension at the beginning of preswing phase and a decrease in plantar flexion at the end of the preswing phase in older adults compared with young adults. Other studies have confirmed these findings, but without the assessment of the speed dependency (9, 19, 31, 32, 41, 50). The present study replicated the age-related decrease in plantar flexion, but not the age-related increase in hip extension (see Fig. 4, B and A, respectively). However, the age-related decrease in plantar flexion was minor compared with the age-related decline in the inter-joint coordination assessed by GWCA (see Fig. 4C). As exemplified in Fig. 4, the inter-joint coordination (i.e., median \( R_t \)) for the fast gait speed was able to discriminate between all younger and older adults within the preswing phase, which was not possible based on the joint kinematics. Moreover, the intra-stride change in the inter-joint coordination was present on temporal scales ranging from 1/20 to 1/5 of the mean stride cycle, a range that contained only 0.26–19.8% of the spectral power of the individual joint angles series. Consequently, small age-related differences in joint kinematics, which are difficult to trace in both visual inspection and conventional analysis of the gait kinematics, seem to be generated by larger differences in inter-joint coordination assessed by GWCA. In summary, GWCA appears to be more sensitive than kinematics to detect age-related differences in gait.

The age-related decline in the inter-joint coordination within the preswing phase was not present in the loading response phase. The significant difference between \( R_{\text{max}} \) of the loading response and preswing phases for younger adults reflects the requirement of higher inter-joint coordination of the push-off leg to accelerate the center of mass in the walking direction compared with the ground-striking leg that decelerates the center of mass directly after heel strike. Thus the age-related decline of the inter-joint coordination in only the preswing phase may indicate age-related impairments in coordination of the push-off. This suggestion is consistent with earlier studies that indicated a decrease in ankle plantar-flexion moment and
Wavelet transformation

Wavelet coherence

Scale (portion of stride time)

Stride HS Stride HS Stride HS Stride

Correlation $R_t$

Correlation $R_t$

Loading Stance Pre-swing Swing

% of stride

time (sec)

Scale (portion of stride time)
power in the push-off of older persons compared with younger persons (9, 19, 24, 31, 32, 41, 50). Studies of transcranial magnetic stimulation have also shown that activation of inhibitory circuits in the motor cortex during walking impair ongoing interaction between motor cortex and lower limb muscles, leading to lower activation in plantar- and dorsiflexors (5, 7, 37, 44, 45). A recent study furthermore showed a larger spectral power of the EEG for sensorimotor, posterior parietal, and anterior cingulated cortex in the transition between single and double support phases directly prior to the $R_{\text{max}}$ found in the present study (13). The same study indicated larger spectral power in both alpha and beta bands in the contralateral sensorimotor cortex prior to the preswing phase than the loading response phase, mimicking the differences found in $R_{\text{max}}$ in the present study. The spectral coherence analysis of EEG of the leg motor area of the motor cortex and EMG of the tibialis anterior muscle revealed a phase lag in the rhythmical cortical activity and the EMG activity in the 24- to 40-Hz band, suggesting that rhythmical cortical activity is transmitted to the lower leg muscle during walking (38). This particular band seems to be specifically related to human gait, because corticomuscular coherence for the tibialis anterior muscle revealed a phase lag in the rhythmical cortical activity in the sensorimotor cortex that leads to decline in the inter-joint coordination during the preswing phase. The age-related redistribution of median $R_t(s)$ shown in Fig. 2 might also be related to the redistribution of spectral power among the alpha, beta, and gamma bands due to change in the inhibitory activity in the sensorimotor cortex. Further application of GWCA should combine EEG, EMG, and joint kinematics in the investigation of age-related changes in inter-joint coordination during gait.

The decline in the intra-joint coordination (i.e., median $R_t$) for the healthy older persons during the double support phase seems to coincide with instabilities during weight transfer. The weight transfer in human gait is the redirection of the center of mass and occurs both before and after the double support phase in accordance with the increase and decrease in median $R_t$. Ihlen et al. (18) reported that the gait kinematics of healthy older persons were more locally dynamic unstable during the

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**Fig. 2.** A representative example of contour plot of intra-stride change in inter-joint coordination [i.e., median $R_t(s)$] for a young person (A) and a healthy older person (B). Red contours represent strong inter-joint coordination coupling [i.e., large median $R_t(s)$] more pronounced in the preswing of the younger person compared with the older person. SL, same leg; OL, opposite leg.
preswing phase but not in the other phases of the stride cycle. Furthermore, nonlinear time series analysis also indicated more rapid structural changes of gait dynamics for older persons compared with younger persons during the same phase (18). A recent observational study reports that the major cause of falls in older persons in long-term care facilities is incorrect weight transfer (43). Thus impairments in inter-joint coordination during the weight transfer in the preswing phase of elderly...
persons’ gaits might be an important risk factor for falls in older
persons.

There are several limitations related to the GWCA of inter-
joint coordination. First, the present study does not assess the
phase relationships between the joint angle series. The instan-
taneous phase angles can be assessed in $15 \times 15$ phase matrix
similar to the correlation matrix (see Eq. A7 in the APPENDIX),
although these phase angles are more sensitive to the choice of
waveform in the wavelet coherence analysis compared with the
coefficient correlations. Second, the minimum number of
strides necessary for a reliable GWCA of inter-joint coordina-
tion (i.e., the median $R_t$) is not assessed in the present study.
Additional test-retest reliability studies will be required to
derive the minimum number of strides necessary for a robust
estimation of median $R_t$. This fact is especially important for
GWCA of the joint kinematics of patients characterized by
stroke, cerebral palsy, or neurodegenerative diseases who have
limited walking capacity. Third, the median $R_t$ is computed by
combining the stride-by-stride sections of $R_t$ from both the
right and left legs because there is no visual presence of asymmetry.
However, stroke patients and patients with cere-
bral palsy may have relevant asymmetries between the affected
and unaffected leg. In studies of these patient groups, the
median $R_t$ should be computed for the right and the left leg
individually. Fourth, no gold standard exists to compare with
the inter-joint coordination obtained by GWCA. Thus the
present results should be replicated by coherence analysis
based on other types of time-frequency decomposition such as
short-time Fourier transform or Wigner-Ville transforms.

Conclusions

The present study introduced GWCA for the assessment of
inter-joint coordination in the gait of young and older adults.
GWCA indicated a decline in inter-joint coordination during
the preswing phase in the gait of older persons. The inter-joint
coordination assessed by GWCA differentiated better between
younger and older adults than the individual joint kinematics.
However, the present study cannot conclude anything about the
physiological mechanisms behind the intra-stride change in
inter-joint coordination or whether the age-related differences in
inter-joint coordination are detrimental or not. Nevertheless,
the inter-joint coordination assessed by GWCA might be an
important tool for early indications of functional decline in the
older population but can also be applied to other muscular and
neurological measurements such as multichannel EMG and
EEG assessed during gait.

Table 2. $F$ and $P$ values for unbalanced two-way ANOVAs
for the age and speed dependency of $R_{max}$ in the loading
response and preswing phase and $R_{min}$ in the stance and
swing phase

<table>
<thead>
<tr>
<th></th>
<th>Age</th>
<th>Speed</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$F$</td>
<td>$P$</td>
</tr>
<tr>
<td>$R_{max}$</td>
<td>6.9</td>
<td>0.01</td>
</tr>
<tr>
<td>$R_{min}$</td>
<td>13.4</td>
<td>0.0005</td>
</tr>
<tr>
<td>Preswing ($R_{max}$)</td>
<td>144.8</td>
<td>&lt;0.00001</td>
</tr>
<tr>
<td>Swing ($R_{min}$)</td>
<td>0.44</td>
<td>0.51</td>
</tr>
</tbody>
</table>

Note that the post hoc pairwise comparison using independent-sample $t$-tests
are presented in Fig. 3, top.

APPENDIX

Technical Details of the Generalized Wavelet Coherence Analysis

The generalized wavelet coherence analysis (GWCA) of $m$ signals
$x_i$ consists of five steps. The following Steps 1 to 3 represent
the wavelet coherence analysis, whereas Steps 4 and 5 represent
the extension of the wavelet coherence analysis for multiple signals $m$
by correlation matrix method:

Step 1: All $m$ signals $x_i$ are decomposed into wavelet coefficients
$W_i^s(t)$ in the time-scale domain by a continuous wavelet transforma-
tion (12, 48):

$$W_i^s(t) = \sqrt{\sum_{j=1}^{N} s_j \cdot \phi_0 \left( \frac{t - \tau}{s} \right)}$$  (A1)

The wavelet $\phi_0$ has a scaled wavelength $s$, and its center $t$
is allowed to slide along the time axis. The wavelet coefficient at time $t$
and scale $s$ is the square mean of product, $x_i \cdot \phi_0$, across all $N$ time
points $t'$ of the signal $x_i$. Equation A1 is called a convolution product
and defines how well the signal $x_i$ correlates with the chosen wavelet
$\phi_0$ at time instant $t$. In contrast to a sine function used in Fourier
transformation, a wavelet function must level off to zero and have
finite extension to decompose the signal $x_i$ into both the time
and frequency domain. The wavelet $\phi_0$ used in the present study
was an analytical Morlet defined by the following equation (12):

$$\phi_0(t) = \pi^{-1/4} e^{i \omega_0 t - 1/2 \omega_0^2}$$  (A2)

The analytical Morlet is a symmetric wave across its centre where
the centre waveform resembles a sine function. The present study
chose $\omega_0$ to provide equivalence between scale $s$ and the period
of the conventional Fourier transform of $x_i$. Similar to the Fourier
transform, the continuous wavelet transform with an analytical Morlet defines
coefficients $W_i^s(t)$ as complex numbers $W_i^s(t) = A_i(s)e^{i\varphi_i(s)}$ with an
amplitude, $A_i(s)$, and phase, $\varphi_i(s)$.

Step 2: The cross-wavelet coefficients $W_i^s(t)$ are defined for all $m^2$
pairs of wavelet coefficients by the following equation (12, 48):

$$W_{ij}^s(t) = W_i^s(t) \overline{W_j^s(t)}$$  (A3)

where $\overline{W_j^s(t)} = A_j(s)e^{i\varphi_j(s)}$ is the complex conjugate of $W_i^s(t)$. The
amplitude $A_i(s)$ of cross-wavelet coefficient $W_{ij}^s(t)$ reflects the co-
variance of signal $x_i$ and $x_j$ at the particular time $t$, and scale $s$ and $\varphi_i(s)$
reflects their phase relationship.

Step 3: The conventional Pearson correlation coefficient is defined by
the covariance of signal $x_i$ and $x_j$ divided by the product of their
standard deviation. In a similar way, wavelet coherence analysis
computes the instantaneous correlation coefficient $R_{ij}^s(t)$ on scale $s$
between signal $x_i$ and $x_j$ by the following equation (12, 48):

$$R_{ij}^s(t) = \frac{\left[ \overline{W_{ij}^s(t)} \right]^{1/2} \left[ W_i^s(t) \overline{W_j^s(t)} \right]^{1/2}}{s^{-1}[W_i^s(t)]^2}$$  (A4)

$s^{-1}[W_i^s(t)]^2$ is the wavelet variance that is the time-scale decom-
position of the signals’ variance where $W_i^s(t) = A_i(s)$ is the amplitude of
the wavelet coefficients and $s^{-1}$ is the inverse scale. The amplitude of
$s^{-1}[W_i^s(t)]^2$ is the wavelet covariance that is the time-scale decom-
position of the covariance between signal $x_i$ and $x_j$. The wavelet variance and
covariance has to be smoothed to prevent the instantaneous correlation
coefficient $R_{ij}^s(t)$ from becoming $1$ across all times and scales (29). The
smoothing operator $S_{\delta} = S_{\delta}[S_{\delta}]$ works along both the scale ($S_{\delta}$)
and time axis ($S_{\delta}$) of the wavelet variance and covariance. The smoothing
operators, $S_{\delta}$ and $S_{\delta}$, have to resemble the shape of the Morlet to preserve
time-scale resolution of the wavelet variance and covariance. Thus, in the
present study, $S_{\delta}$ and $S_{\delta}$ were defined according to the Morlet in Eq. A2
by the following two equations (12, 48):

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\[
S\left[ W_i(s) \right] = W_i(s) \odot c_1 \Pi(0.6s) \tag{A5a}
\]
\[
S\left[ W_i(s) \right] = W_i(s) \odot c_2 \frac{1}{2s} \tag{A5b}
\]

where \( \odot \) and \( \oplus \) is the convolution across scale and time axis, respectively, \( c_1 \) and \( c_2 \) are normalization constants and \( \Pi \) is the rectangular function.

**Step 4:** The correlation matrix method arranges all instantaneous correlation coefficients \( R_{ij}(s) \) into the following instantaneous correlation matrix \( C_i(s) \) after the wavelet coherence analysis has been performed on all \( m^2 \) pairs of signal (40):

\[
C_i(s) = \begin{bmatrix}
R_1^{s_{1}i}(s) & \cdots & R_1^{s_{m}i}(s) \\
\vdots & \ddots & \vdots \\
R_m^{s_{1}i}(s) & \cdots & R_m^{s_{m}i}(s)
\end{bmatrix} \tag{A6}
\]

The phase relationship between each signal pair is defined as the phases \( \phi_{ij}(s) \) of the cross-wavelet coefficients \( W_{ij}(s) \) and can be arranged in a instantaneous phase matrix that corresponds to \( C_i(s) \):

\[
\phi_i(s) = \begin{bmatrix}
\phi_1^{s_{1}i}(s) & \cdots & \phi_1^{s_{m}i}(s) \\
\vdots & \ddots & \vdots \\
\phi_m^{s_{1}i}(s) & \cdots & \phi_m^{s_{m}i}(s)
\end{bmatrix} \tag{A7}
\]

**Fig. 4.** Comparison of hip flexion-extension (A), ankle plantar- and dorsiflexion (B), and inter-joint coordination \( R \) (C) assessed by GWCA for all young (blue traces) and older participants (red traces) on the fast gait speed.
Step 5: The instantaneous correlation matrix $C_i(s)$ is then reduced to a diagonal matrix of $m$ instantaneous eigenvalues:

$$C_i(s) = \begin{bmatrix} \lambda_1(s) & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \lambda_m(s) \end{bmatrix} \quad (A8)$$

Each of the eigenvalue $\lambda_i(s)$ reflects the general relationship of a signal to all other $m-1$ signals for scale $s$ and time $t$. The eigenvalues have to be converted into a general instantaneous correlation coefficient to decide the strength of this general relationship. However, a conversion from the eigenvalues of $C_i(s)$ to a general instantaneous correlation coefficient $R_i(s)$ only exists for the maximum eigenvalue by the following equation (40):

$$R_i(s) = \frac{1}{m-1} \left[ \lambda_{i\text{max}}(s) - 1 \right] \quad (A9)$$

where $\lambda_{i\text{max}}(s)$ is the maximum eigenvalue of $C_i(s)$. The general instantaneous correlation coefficient $R_i(s)$ numerical defines the time-scale decomposition of the strongest relationship between all $m$ signals. Furthermore, $R_i(s)$ is equivalent with the instantaneous correlation coefficient of Eq. A4 in the special case when $m = 2$ (40).

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DISCLOSURES

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AUTHOR CONTRIBUTIONS

Author contributions: E.A.F.I. conception and design of research; E.A.F.I. performed experiments; E.A.F.I. analyzed data; E.A.F.I. interpreted results of experiments; E.A.F.I. prepared figures; E.A.F.I. drafted manuscript; E.A.F.I. edited and revised manuscript; E.A.F.I. approved final version of manuscript.

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