

# Statistical criteria for estimation of the cerebral autoregulation index (ARI) at rest

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## Abstract

The autoregulation index (ARI) can reflect the effectiveness of cerebral blood flow (CBF) control in response to dynamic changes in arterial blood pressure (BP), but objective criteria for its validation have not been proposed. Monte Carlo simulations were performed by generating five minute long random input/output signals that mimic the properties of mean beat-to-beat BP and CBF velocity (CBFV) as usually obtained by non-invasive measurements in the finger (Finometer) and middle cerebral artery (transcranial Doppler ultrasound), respectively. Transfer function analysis (TFA) was used to estimate values of ARI by optimal fitting of template curves to the output (or CBFV) response to a step change in input (or BP). 2-step criteria were adopted to accept estimates of ARI as valid. The 95% confidence limit of the mean coherence function (0.15-0.25 Hz) ( $\gamma^2_{crit}$ ) was estimated from 15,000 runs, resulting in  $\gamma^2_{crit} = 0.190$  when using five segments of data, each with 102.4 s (512 samples) duration (Welch's method). This threshold for acceptance was dependent on the TFA settings and increased when using segments with shorter duration (51.2 s). For signals with mean coherence above the critical value, the 5% confidence limit of the normalised mean square error (NMSE<sub>crit</sub>) for fitting the step response to Tieck's model, was found to be approximately 0.30 and independent of the TFA settings. Application of these criteria to physiological and clinical sets of data showed their ability to identify conditions where ARI estimates should be rejected, for example due to CBFV step responses lacking physiological plausibility. A larger number of recordings were rejected from acute ischaemic stroke patients than for healthy volunteers. More work is needed to validate this procedure with different physiological conditions and/or patient groups. The influence of non-stationarity in BP and CBFV signals should also be investigated.

## Keywords

Cerebral blood flow, Monte Carlo simulation, transfer function analysis, coherence function, transcranial Doppler ultrasound

## 1. Introduction

The cerebral autoregulation index (ARI) was introduced by Rune Aaslid and co-workers (Tiecks *et al.*, 1995) as a metric to assess the effectiveness of cerebral dynamic autoregulation (CA) in physiological and clinical studies. CA is a potent regulatory mechanism that maintains cerebral blood flow (CBF) within narrow limits, despite changes in mean arterial blood pressure (MBP) (Paulson *et al.*, 1990; Panerai, 1998). Originally regarded as a static mechanism (Lassen, 1959), more recent studies of CA have focused on its dynamic properties, as reflected by the transient response of CBF velocity (CBFV), usually measured with transcranial Doppler ultrasound (Panerai, 2009), following sudden changes in MBP (Aaslid *et al.*, 1989). In its original formulation, the ARI was derived by best fitting one of 10 different template curves to the CBFV response following a sudden drop in MBP, induced by the rapid deflation of thigh cuffs (Aaslid *et al.*, 1989; Tiecks *et al.*, 1995). Each template curve results from a combination of parameters derived from a second order differential equation model leading to values of ARI ranging from 0 (absence of CA) to 9 (best observed CA). In parallel with these developments, transfer function analysis (TFA) was proposed to model the dynamic MBP-CBF relationship as a frequency-dependent phenomenon (Giller, 1990; Zhang *et al.*, 1998), based on spontaneous fluctuations in MBP and CBFV at rest. Compared to the use of inflated thigh cuffs, measurements performed at rest present considerable advantages regarding comfort for subjects, stability of physiological conditions, and the ability to perform repeated observations (Panerai, 1998). The attractive possibility of deriving ARI from spontaneous fluctuations at rest was demonstrated in 1998, based on the CBFV response to a step change in MBP calculated with the inverse Fourier transform of transfer function estimates of amplitude and phase frequency responses (Panerai *et al.*, 1998). From there on, several studies have adopted this approach to combine the compactness of the ARI scale with the advantages of recordings at rest (Panerai, 2008). Clinical applications of this approach have shown that compared to healthy subjects, ARI is reduced in patients with carotid artery disease (Panerai *et al.*, 1998), severe head injury (Panerai *et al.*, 2004), ischaemic stroke (Salinet *et al.*, 2014), and preeclampsia (Van Veen *et al.*, 2015). Moreover, in healthy subjects, ARI estimated from spontaneous MBP fluctuations was shown to be reduced by hypercapnia (Katogridakis *et al.*, 2013), pre-syncope (Carey *et al.*, 2001) and hypobaric hypoxia (Subudhi *et al.*, 2010). Despite its considerable potential, the accuracy of ARI estimates has been of concern. Firstly, as it comprises a 'closed' scale (0-9), unreliable estimates, as for example resulting from recordings with low signal-to-noise ratio (SNR), cannot be spotted as outliers. Secondly, a bootstrap approach demonstrated ARI has limited consistency to differentiate between neighbouring values (Simpson *et al.*, 2004). Finally, and consistent with (Simpson *et al.*, 2004), a reproducibility study indicated that at least 44 subjects need to be enrolled in each group to detect a difference in ARI of 1-unit with satisfactory statistical power (Brodie *et al.*, 2009). These limitations of ARI have been mitigated by closer scrutiny of the robustness of TFA estimates, by checking the statistical significance of the coherence function (Gommer *et al.*, 2010), as well as visual inspection of the CBFV step response, to

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3 guarantee its physiological plausibility (Panerai *et al.*, 2004; Van Veen *et al.*, 2015). This approach  
4 has led to satisfactory results, but its subjectivity can lead to bias and inconsistencies amongst  
5 operators. A previous attempt to address this problem only included neonatal data and did not  
6 consider ARI estimation (Ramos *et al.*, 2006). As an attempt to overcome the limitations outlined  
7 above, we have performed Monte Carlo simulations to establish robust confidence limits for the  
8 coherence function derived by TFA and also for ARI, based on the quality of fitting of the model of  
9 Tiecks *et al* (Tiecks *et al.*, 1995). The applicability of these new statistical criteria to real data was  
10 tested on a set of recordings from healthy subjects as well as in ischaemic stroke patients.  
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## 20 2. Methods

### 21 22 23 *Surrogate data*

24 Random time-series of input and output signals were generated with 300 s duration that mirrored the  
25 properties of MBP and CBFV signals, often recorded for periods of five minutes at rest. For each run,  
26 two separate series of gaussian noise with 10% coefficient of variation were generated for input and  
27 output, and low-pass filtered with a zero-phase 8<sup>th</sup> order Butterworth filter with cut-off frequency of  
28 0.25 Hz. To follow the standard procedure for interpolation and resampling of cardiovascular  
29 recordings, a separate random series was generated to play the role of pulse-interval. Using this  
30 sequence with both the input and output random signals, interpolation was performed with a third  
31 order polynomial followed by resampling at 5Hz to generate signals with a uniform time base  
32 (Katogridakis *et al.*, 2013). The TFA and statistical procedures performed on these signals are  
33 described later.  
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### 42 *Physiological data*

43 Adult subjects without any symptoms or history of neurological or cardiovascular disease were  
44 recruited from departmental staff and patient relatives. The study received ethical approval  
45 (Northampton REC, ref 11/EM/0369) and all participants gave written informed consent.  
46 Participants did not have a heavy meal or caffeinated products for at least two hours before attending  
47 a temperature controlled (20-23 °C) laboratory that was free of distraction. They rested supine for at  
48 least 20 minutes before any measurements were performed. Continuous non-invasive arterial blood  
49 pressure (BP) was recorded with arterial volume clamping of the digital artery (Finometer, Finapres  
50 Systems, Amsterdam, The Netherlands); bi-lateral CBFV in the middle cerebral artery (MCA) was  
51 measured with transcranial Doppler ultrasound (Viasys Companion III, Viasys Health Care, San  
52 Diego CA, USA) at depths of insonation in the range 50-60 mm using a head-frame to fix 2 MHz  
53 probes over the temporal windows. A 3-lead ECG was continuously recorded using the add-on feature  
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3 of the Finometer. End-tidal CO<sub>2</sub> was measured with an infra-red capnograph (Capnocheck Plus)  
4 using nasal prongs.  
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7 At the beginning of each recording, lasting a minimum of five minutes, the servo calibration of the  
8 Finometer was switched off; systolic and diastolic BP values obtained by brachial  
9 sphygmomanometry (OMRON 705IT) were used to calibrate the continuous BP signal offline. All  
10 signals were simultaneously recorded and transferred to a computer at a rate of 500 samples/s for each  
11 channel.  
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#### 14 15 16 *Clinical data*

17 Data representative of the more challenging conditions prevailing during recordings in critically ill  
18 patients were obtained from a previous study (Salinet *et al.*, 2014). Patients with a first episode of  
19 ischaemic stroke were studied in the first 72 hours of symptom onset. Exclusion criteria were a history  
20 of neurological disease, atrial fibrillation or severe cognitive impairment. The study received ethical  
21 committee approval (Nottingham REC, ref. 11/EM/0016) and all subjects gave informed consent. For  
22 the purposes of the present study, measurements were performed in the same laboratory as for the  
23 physiological data described previously, using the same equipment and procedure to record a five-  
24 minute set of baseline data. In a sub-group of patients recruited at the beginning of the study, BP  
25 recordings were performed with the Finapres device (Ohmeda 2300, Louisville CO, USA).  
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#### 33 34 *Data analysis*

35 TFA was performed for each pair of surrogate signals using the classical FFT approach combined  
36 with Welch's method (Welch, 1967). Choice of parameter settings followed the recommendations of  
37 the International Cerebral Autoregulation Research Network (CARNet) (Claassen *et al.*, 2015). A  
38 five-minute baseline recording allowed the use of five 102.4 s (512 samples) segments of data, with  
39 50% superposition. The mean value of each segment was removed and a cosine window was applied  
40 to reduce spectral leakage. Additional spectral smoothing was obtained with a 3-point moving average  
41 triangular filter applied to both input and output amplitude spectra. In the frequency domain, only the  
42 squared coherence function was considered further with calculation of its mean value in the frequency  
43 range 0.15-0.25 Hz ( $\gamma^2_m$ , see Discussion). The CBFV response to a step change in MBP was estimated  
44 from the inverse FFT of the transfer function as described previously (Panerai *et al.*, 1998; Panerai *et*  
45 *al.*, 2004). The step response template curves proposed by Tiecks *et al* (Tiecks *et al.*, 1995) were  
46 fitted to the CBFV step response for the duration of 8 s after its beginning. The template curve  
47 corresponding to the minimum mean square error (MSE) determined the corresponding value of ARI.  
48 Parabolic interpolation using neighbouring values of the optimal ARI was employed to obtain  
49 estimates with two decimal places. The MSE was normalised (NMSE) by the amplitude of the CBFV  
50 step response and used to estimate its 95% confidence limits as described later. In addition to the  
51 standard setting of five segments of data with  $N_L=512$  samples, simulations were also performed with  
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3  $N_L=256$  samples and with the number of segments ( $N_{\text{SEGM}}$ ) ranging from 3 to 8. In this case, longer  
4 sequences of random data were generated as needed.  
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8 Both physiological and clinical data were edited as described previously (Katogridakis *et al.*, 2013;  
9 Salinet *et al.*, 2014). In short, the continuous, raw measurements of BP and CBFV were visually  
10 inspected and any spikes or artefacts with duration  $< 100$  ms were linearly interpolated. The CBFV  
11 signal was low-pass filtered with a median filter and all signals were low-pass filtered with an 8<sup>th</sup>  
12 order, zero-phase Butterworth filter with cutoff frequency of 20 Hz. Using the ECG to mark the  
13 occurrence of each cardiac cycle, mean values of BP and CBFV were obtained for each heartbeat. The  
14 pulse interval sequence was then used to obtain a 5 Hz uniform time base for MBP and mean CBFV  
15 as described above. TFA of the measured signals followed the same procedure described above for  
16 surrogate data with each subject thus providing estimates of mean squared coherence ( $\gamma_m^2$ ), ARI and  
17 NMSE for fitting the Tiecks *et al* model (Tiecks *et al.*, 1995).  
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### 28 *Statistical procedure*

29 Fifteen thousand runs were performed with surrogate data to generate corresponding pairs of  $\gamma_m^2$  and  
30 NMSE values. The 95% upper confidence limit of  $\gamma_m^2$  was estimated by linear interpolation of the  
31 histogram with bin width equal to 0.02; referred to as  $\gamma_{\text{crit}}^2$ . Using a similar procedure, the 5% lower  
32 confidence limit of NMSE ( $\text{NMSE}_{\text{crit}}$ ) was determined by the distribution of values after the condition  
33  $\gamma_m^2 > \gamma_{\text{crit}}^2$  was met. This process was repeated for combinations of  $N_L$  (256 or 512) and  $N_{\text{SEGM}}$  (3 to  
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40 For each physiological or clinical recording, values of  $\gamma_m^2$  and NMSE were compared to  $\gamma_{\text{crit}}^2$  and  
41  $\text{NMSE}_{\text{crit}}$  for the standard condition ( $N_L=512$  samples,  $N_{\text{SEGM}}=5$ ). Corresponding estimates of ARI  
42 were considered acceptable if  $\gamma_m^2 > \gamma_{\text{crit}}^2$  and  $\text{NMSE} < \text{NMSE}_{\text{crit}}$ . The distribution of ARI for recordings  
43 found to be acceptable was described by its mean (SD), and differences between estimates for the  
44 right and left MCA were assessed with the paired Student's t-test. Values of  $p < 0.05$  were considered  
45 significant.  
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49 CBFV step responses were visually inspected by one of the authors (RBP) and classified as either  
50 'physiological' or not (Ramos *et al.*, 2006). Responses were classified as 'non-physiological' if the  
51 initial upstroke was negative or missing (slow continuous rise), or the recovery phase led to negative  
52 values with absolute values greater than half the amplitude of the initial upstroke.  
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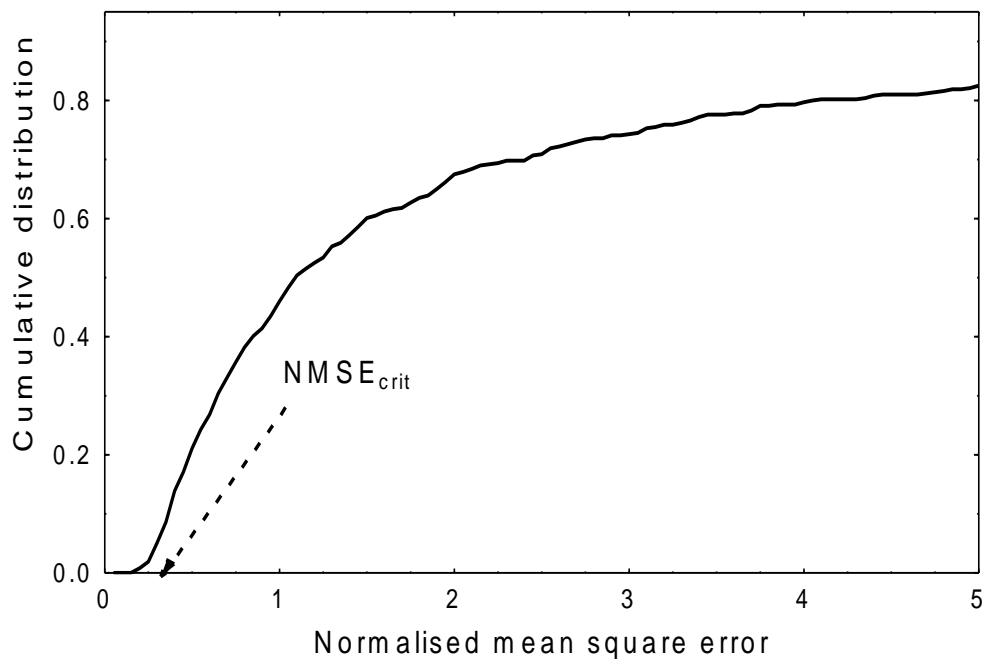
### 3. Results

#### *Surrogate data*

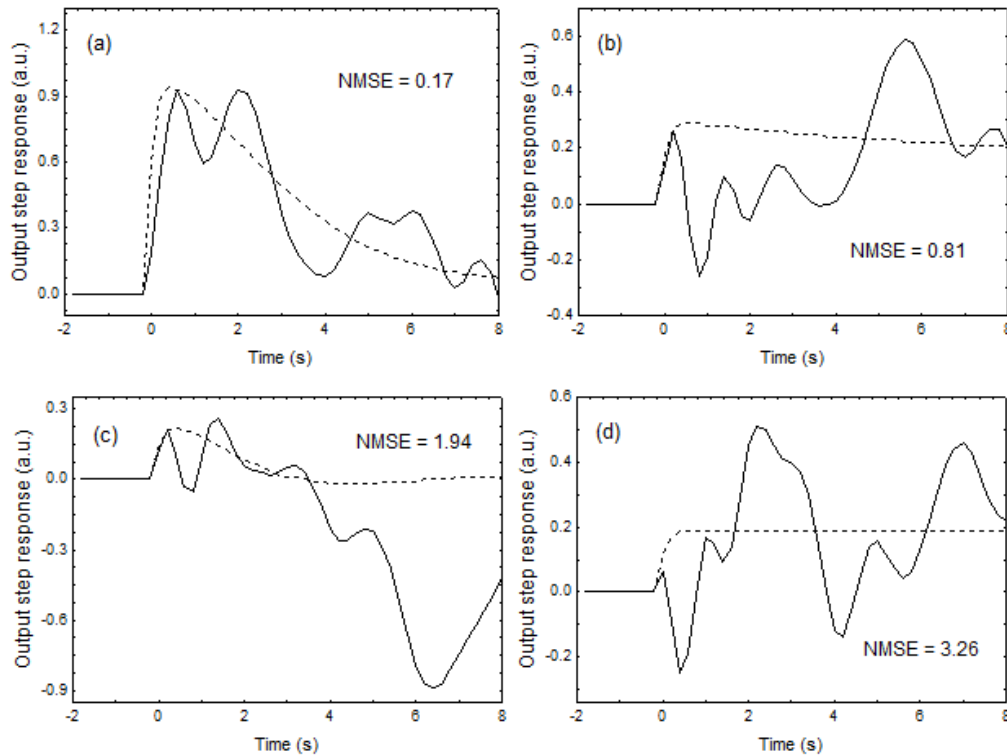
Values of  $\gamma_{crit}^2$  are given in Table 1 for different combinations of  $N_{SEGM}$  and  $N_L$ . As expected, these values tend to decrease with increasing number of degrees of freedom. For the standard setting ( $N_{SEGM}=5$ ,  $N_L=512$ ), the distribution of NMSE is given in Fig. 1. Differently from  $\gamma_{crit}^2$ ,  $NMSE_{crit}$  showed random fluctuations after each 15,000 runs but did not change significantly with either  $N_{SEGM}$  or  $N_L$ . For different combinations ( $n=24$ ), including changes in the random number generator seed value, the mean (SD) of  $NMSE_{crit}$  was 0.308 (0.026). For simplicity,  $NMSE_{crit}=0.30$  was adopted for the standard setting. Visual inspection of 145 output step responses with  $\gamma_m^2 > 0.190$  (standard setting) showed that all cases with  $NMSE < 0.3$  were classified as ‘physiological’. On the other hand, for  $NMSE > 0.3$ , the number of ‘non-physiological’ responses tended to increase with NMSE. For NMSE in the interval [0.3,0.6], 41.7% were ‘non-physiological’, but this rate reached 90.9% for  $NMSE > 1.2$ . Fig. 2 illustrates the deterioration of the output step response with increasing values of NMSE. According to the  $NMSE < 0.30$  criterion, the response in Fig. 2(a) would be accepted, but the other three examples would be automatically rejected.

**Table 1** – Values of the 95% upper confidence limit for mean squared coherence in the frequency range 0.15-0.25 Hz ( $\gamma_{crit}^2$ ) for surrogate data estimated from 15,000 runs with different values of  $N_{SEGM}$  and  $N_L$ . The shaded cell indicates the standard condition recommended for dynamic cerebral autoregulation studies (Claassen *et al.*, 2015).

$N_{SEGM}$	$N_L=256$	$N_L=512$
3	0.358	0.292
4	0.300	0.228
5	0.242	0.190
6	0.207	0.164
7	0.176	0.142
8	0.152	0.127



**Figure 1** – Cumulative distribution of the normalised mean square error (NMSE) for recordings with mean squared coherence (range 0.15-0.25 Hz) greater than the 95% upper confidence limit ( $\gamma^2_{\text{crit}} = 0.190$  for  $N_{\text{SEGM}}=5$ ,  $N_L=512$  samples). The arrow indicates the position of the 5% lower confidence limit for NMSE ( $\text{NMSE}_{\text{crit}} = 0.30$ ).

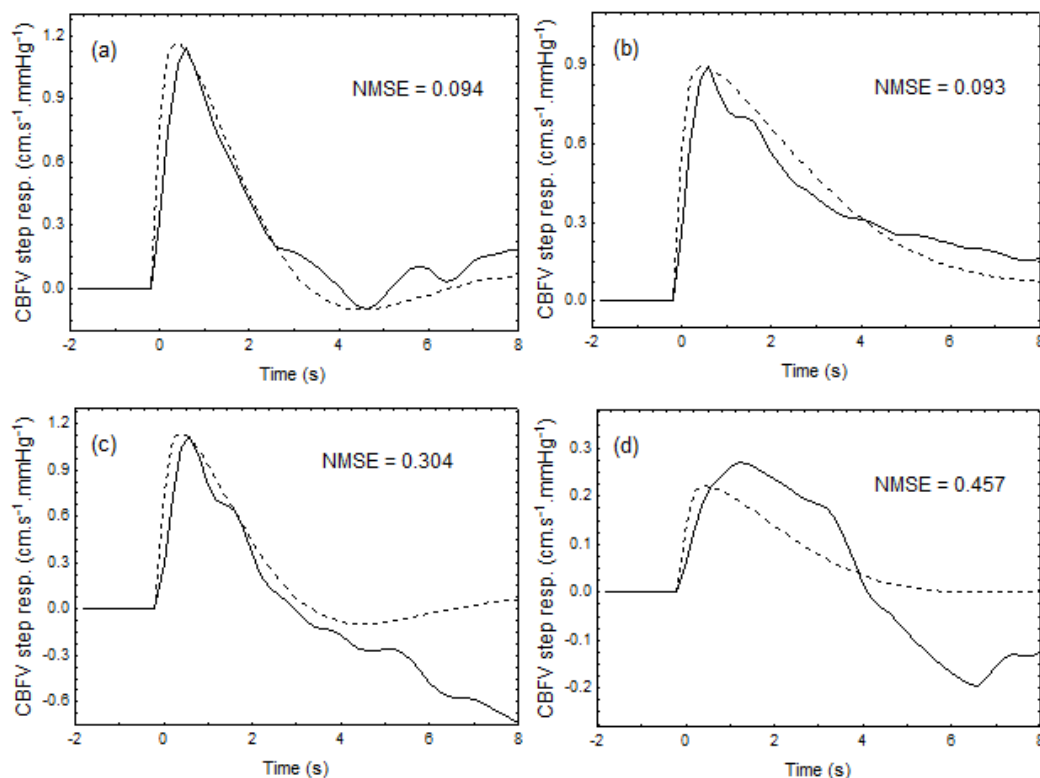


**Figure 2** – Representative output step responses (continuous line) obtained from surrogate random data for increasing values of the normalised mean square error (NMSE) and best fit Tiecks model (dashed line). According to the  $NMSE < 0.30$  criterion, the step response in (a) would be accepted, but the ones in (b-d) would be rejected. In all cases the mean coherence criterion ( $\gamma_m^2 > \gamma_{crit}^2$ ) was satisfied.

### Physiological data

Good quality recordings were obtained in 59 subjects (33 males) with mean (SD) age of 62.6 (10.6) years. For this group, systolic/diastolic BP was 127.7 (19.6)/72.2 (9.9) mmHg; CBFV 51.7 (13.1) and 51.0 (12.2) cm/s for the right and left MCAs, respectively. For  $N_{SEGM}=5$  and  $N_L=512$ , all recordings had  $\gamma_m^2 > 0.190$  for both hemispheres. However, for the right MCA, three recordings had  $NMSE > 0.3$  whilst for the left MCA there were four such recordings. As a result, there were 54 complete pairs of ARI values corresponding to 5.09 (1.67) and 5.34 (1.53) for the right and left MCAs, respectively. The paired t-test confirmed a non-significant difference between hemispheres. Fig. 3 provides examples of CBFV step responses from the left MCA in four different healthy subjects.

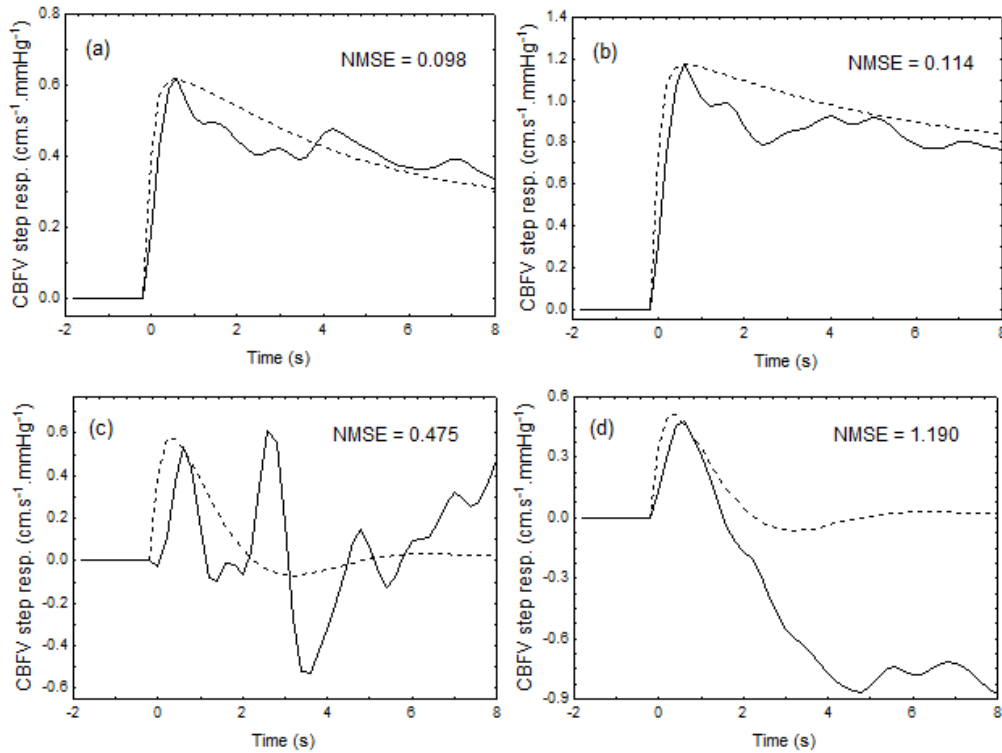




**Figure 3** – Representative CBFV step responses (continuous line) in physiological recordings and best fit Tiecks model response (dashed line). The two top cases (a & b) satisfy the normalised mean square error criterion ( $\text{NMSE} < 0.30$ ) and would be accepted in further analyses. (c) Example of a borderline response with  $\text{NMSE} \cong 0.3$ . The response in (d) has  $\text{NMSE} > 0.30$  and hence would be rejected. For the accepted responses the corresponding values of ARI are 7 (a) and 5 (b), respectively.

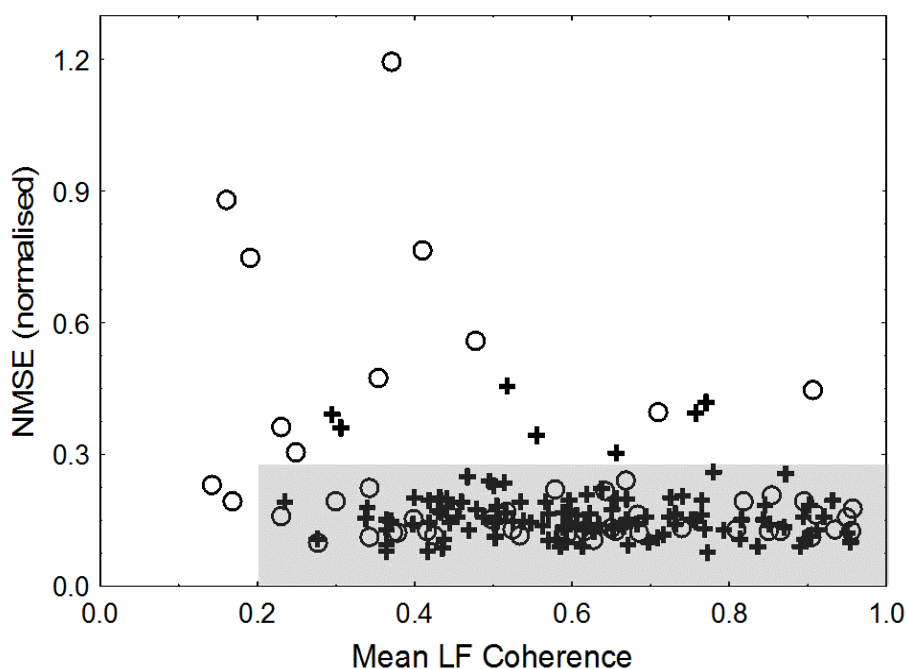
#### *Clinical data*

Twenty-six (14 male) recordings of acceptable quality were obtained in acute ischaemic stroke patients with mean (SD) age 63.4 (11.7) years. Systolic/diastolic BP were 146.7 (28.4)/63.9 (13.2) mmHg; CBFV was 40.9 (14.7) and 43.9 (20.7)  $\text{cm/s}$  for the right and left MCAs, respectively. For the right MCA, all recordings had  $\gamma_m^2 > 0.190$ , but for the left side two subjects did not reach the critical value of mean coherence. With the NMSE criterion, five recordings from the right MCA and another six from the left MCA were rejected for being above the  $\text{NMSE}_{\text{crit}}$  threshold. The resulting values of ARI were 5.40 (2.12) and 5.24 (1.97), for the right and left MCAs, respectively. Comparing the two sides in this group of subjects was not deemed appropriate as discussed below. Fig. 4 provides examples of CBFV step responses from the left MCA in four different stroke patients.



**Figure 4** – Representative CBFV step responses (continuous line) in clinical recordings and best fit Tiecks model (dashed line). The two top cases (a & b) satisfy the normalised mean square error criterion ( $NMSE < 0.30$ ) and would be accepted in further analyses. The responses in (c & d) have  $NMSE > 0.30$  and hence would be rejected. For the accepted responses, the corresponding values of ARI are 2.9 (a) and 2.4 (b), respectively.

Treating each hemisphere as an independent estimate of ARI led to a total of 5.93 % (7/118) of values rejected in healthy subjects and 25% (13/52) in the patient group (Fig. 5), indicating a highly significant difference ( $p=0.0004$ ) in the rate of rejection according to the joint criteria.



**Figure 5** – Combined distribution of NMSE versus mean squared coherence (range 0.15-0.25 Hz) for physiological (circles) and clinical data (crosses). Both hemispheres are included for all subjects. The region of acceptance is indicated by the shaded area.

#### 4. Discussion

##### *Surrogate data*

The main contribution of this study is the proposal of a statistically robust procedure for acceptance of estimates of ARI derived by TFA of spontaneous fluctuations of MBP and CBF. At each harmonic, the squared coherence function represents the fraction of output power that can be linearly explained by the input power. Values of coherence will approximate 1.0 for linear univariate systems if measurements have high SNR. On the other hand, in the presence of strong non-linearities, multiple inputs, or poor SNR, the coherence will approach zero. Based on these properties, the 95% upper confidence limit of  $\gamma^2(f)$  has been proposed as a suitable threshold to accept TFA estimates of gain and phase frequency responses (Benignus, 1969; Gommer *et al.*, 2010; Claassen *et al.*, 2015). In most previous studies though, this approach has been limited to single harmonics with the objective of accepting or rejecting values of gain and/or phase. A different situation however, occurs with estimates of ARI. Since the inverse FFT of the TFA includes all harmonics, it is not possible to delete individual harmonics from the analysis. Moreover, mean values of coherence cannot be used over the entire spectrum due to the well-known non-linearity of dynamic CA in the frequency range where cerebral autoregulation is active, that is usually accepted as limited to frequencies below 0.10-0.15 Hz (Panerai *et al.*, 2006). For this reason, we adopted the 0.15-0.25 Hz range to obtain mean values of

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3 coherence to determine the statistical significance of the MBP-CBFV relationship as quantified by  
4 TFA. The upper limit of 0.25 Hz is a suitable choice due to the limited bandwidth of MBP and CBFV  
5 beat-to-beat signals. The values presented in Table 1 are in very good agreement with previous work,  
6 when the increased number of degrees of freedom resulting from the average of several harmonics is  
7 taken into account (Claassen *et al.*, 2015). Noteworthy, rigorous application of the  $\gamma^2_{\text{crit}}$  criterion will  
8 need to take into account the individual values of  $N_{\text{SEGM}}$  and  $N_L$  adopted in each case.  
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### 13 *Physiological data*

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15 Blind application of the criteria derived from Monte Carlo simulations to a set of data from healthy  
16 subjects achieved similar results as our previous procedure involving visual inspection of the  
17 complete coherence function and also the temporal pattern of the CBFV step response (Brodie *et al.*,  
18 2009; Katogridakis *et al.*, 2013; Salinet *et al.*, 2014). As expected from high quality recordings  
19 obtained under ideal conditions, all subjects had mean coherence values above the 95% confidence  
20 limit. Nevertheless, some of the CBFV step responses had temporal patterns that were not  
21 physiologically plausible as illustrated in Fig. 3(c) and 3(d). For responses of this nature, the  
22 automatic procedure for acceptance or rejection based on objective criteria is an important advantage  
23 as it rules out subjective decisions that could lead to biases and erroneous conclusions. The responses  
24 illustrated in Fig. 3(c) and 3(d) are good examples of cases where individual investigators may not  
25 agree about a decision to accept or reject the corresponding ARI estimates.  
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### 36 *Clinical data*

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38 The inclusion of data from acute ischaemic stroke patients had the objective of testing the application  
39 of the new acceptance criteria of ARI estimates to recordings obtained under more difficult  
40 conditions, such as in critically ill patients. The use of this dataset for investigating the effectiveness  
41 of dynamic CA in stroke patients was reported elsewhere (Salinet *et al.*, 2014) and is beyond the  
42 scope of this study. These data are representative of the difficulties of obtaining stable recordings at  
43 rest in subjects who can be confused, agitated and not able to cooperate or understand instructions  
44 clearly. As expected, the SNR of these measurements was not as high as those obtained with healthy  
45 subjects; as a consequence not all patients had values of mean coherence above the critical threshold.  
46 Moreover, the number of CBFV step responses with NMSE above the 5% lower confidence limit  
47 (NMSE<sub>crit</sub>=0.30) was also significantly higher compared to physiological recordings. Although some  
48 CBFV step responses are strikingly ‘non-physiological’ (Fig. 4(c) and 4(d)), the risk of introducing  
49 bias due to subjective decisions is as high as with physiological data. However, the potentially  
50 damaging consequences of this are even greater in clinical studies, where smaller sample sizes mean  
51 that a few misclassifications can produce misleading results.  
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3 Due to lateralization of the ischaemic region, inter-hemispheric comparisons were not deemed  
4 appropriate in this case nor was the separation of hemispheres into affected/unaffected, given the main  
5 objectives of the present study.  
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#### 8 9 10 *Limitations of the study*

11 Although Monte Carlo simulation is a powerful tool to derive properties of stochastic distributions,  
12 restraint is needed so as not to extend conclusions beyond its underlying assumptions. In our case,  
13 random surrogate data were generated by processes consistent with those of real measurements of BP  
14 and CBFV, but did not include the presence of non-stationarities, for example variable levels of BP  
15 power. More work is needed to test the sensitivity of the confidence limits of  $\gamma^2_m$  and NMSE to the  
16 presence of non-stationarities in the MBP and CBFV time series. One alternative to Monte Carlo  
17 simulations would be the computation of the exact confidence limits of coherence as proposed by  
18 Wang and Tang (2004).  
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21 Our results are also confined to ARI estimates based on transfer function analysis of spontaneous  
22 fluctuations in BP and CBFV. As a consequence, three important restrictions need to be kept in mind.  
23 First, different values of  $\gamma^2_{crit}$  might result from different physiological conditions, such as the squat-  
24 stand test (Smirl *et al.*, 2015). Secondly,  $NMSE_{crit}$  was derived for CBFV step responses obtained  
25 from the inverse transform of the transfer function. For step responses estimated by other methods,  
26 such as autoregressive-moving average models (Panerai *et al.*, 2003), different NMSE thresholds  
27 might apply. Finally, neither criterion ( $\gamma^2_{crit}$  or  $NMSE_{crit}$ ) can be used if values of ARI are to be  
28 obtained by direct application of Tiecks *et al.* (Tiecks *et al.*, 1995) equations to the MBP and CBFV  
29 time series.  
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32 The effectiveness of the selection criteria proposed also needs to be tested more widely, including in  
33 different patient groups and subjects whose breathing patterns might increase MBP variability and  
34 power in the 0.15-0.25 Hz frequency range. The latter is likely to shift the mean coherence  
35 distribution upwards and lead to different values of  $\gamma^2_{crit}$  and  $NMSE_{crit}$ .  
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#### 39 40 41 42 43 44 45 46 47 48 **5. Conclusions**

49 Objective and robust estimates of ARI, obtained with TFA of spontaneous fluctuations in BP and  
50 CBF, require confirmation of the statistical significance of the coherence function, as well as strict  
51 control of the quality of fitting of the CBFV step response to the standard template curves that  
52 correspond to the different values of this index (Tiecks *et al.*, 1995). To apply the criterion based on  
53 the 95% confidence limit for the mean value of coherence in the frequency range 0.15-0.25 Hz, it is  
54 necessary to take into consideration the number of data segments used for smoothing (Welch, 1967)  
55 and the duration (number of data samples) of each segment. On the other hand, the criterion based on  
56 the NMSE for fitting the CBFV step response to Tiecks *et al.* (Tiecks *et al.*, 1995) model is  
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3 independent of the TFA settings. Further work is needed to assess the generalizability of these criteria  
4 to different physiological conditions and patient populations. Objective criteria for acceptance of ARI  
5 estimates are of considerable importance to improve observer reliability and to minimize the risk of  
6 bias in physiological and clinical studies.  
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### 10 11 12 **Acknowledgements**

13 Supported by EPSRC grant EP/K041207/1. The authors would like to thank Professor DM Simpson  
14 (University of Southampton) for his ideas and discussions about the use of bootstrap and Monte Carlo  
15 methods to improve the reliability of techniques to assess dynamic cerebral autoregulation.  
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### 23 **Data Access statement**

24 Due to Ethical Committee requirements for specific patient consent, preceding recent Research  
25 Councils UK directive towards making support data publicly available, it is not possible to make the  
26 support data for this study openly accessible.  
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## References

- 1  
2  
3  
4  
5  
6  
7 Aaslid R, Lindegaard KF, Sorteberg W & Nornes H 1989 Cerebral autoregulation dynamics in humans  
8 *Stroke* **20** 45-52  
9
- 10  
11 Benignus VA 1969 Estimation of the coherence spectrum and its confidence interval using the fast  
12 Fourier transform *IEEE Trans. Audio Electroacoust.* **17** 145-150  
13  
14
- 15 Brodie FG, Atkins ER, Robinson TG & Panerai RB 2009 Reliability of dynamic cerebral autoregulation  
16 measurements using spontaneous fluctuations in blood pressure. *Clin. Sci.* **116** 513-520  
17  
18
- 19  
20 Carey BJ, Manktelow BN, Panerai RB & Potter JF 2001 Cerebral autoregulatory responses to head-up  
21 tilt in normal subjects and patients with recurrent vasovagal syncope *Circulation* **104** 898-  
22 902  
23  
24
- 25 Claassen JAHR, Meel-van den Abeelen ASS, Simpson DM & Panerai RB 2015 Transfer function  
26 analysis of dynamic cerebral autoregulation: a white paper from the International  
27 Autoregulation Research Network (CARNet) *J Cereb. Blood Flow Metabol.* **under review**  
28  
29
- 30  
31 Giller CA 1990 The frequency-dependent behavior of cerebral autoregulation *Neurosurgery* **27** 362-  
32 368  
33  
34
- 35 Gommer ED, Shijaku E, Mess WH & Reulen JPH 2010 Dynamic cerebral autoregulation: different  
36 signal processing methods without influence on results and reproducibility *Med. & Biol. Eng.*  
37 *& Comp.* **48** 1243-1250  
38  
39
- 40  
41 Katogridakis E, Bush G, Fan L, Birch AA, Simpson DM, Allen R, Potter JF & Panerai RB 2013 Detection  
42 of impaired cerebral autoregulation improves by increasing arterial blood pressure  
43 variability *J Cereb. Blood Flow Metab.* **33** 519-523  
44  
45
- 46  
47 Lassen NA 1959 Cerebral blood flow and oxygen consumption in man *Physiol. Rev.* **39** 183-238  
48
- 49  
50 Panerai RB 1998 Assessment of cerebral pressure autoregulation in humans - a review of  
51 measurement methods *Physiol. Meas.* **19** 305-338  
52
- 53  
54 Panerai RB 2008 Cerebral autoregulation: From models to clinical applications *Cardiovasc. Eng.* **8** 42-  
55 59  
56
- 57  
58 Panerai RB 2009 Transcranial Doppler for evaluation of cerebral autoregulation *Clin. Auton. Res.* **19**  
59 197-211  
60

- 1  
2  
3 Panerai RB, Eames PJ & Potter JF 2003 Variability of time-domain indices of dynamic cerebral  
4 autoregulation *Physiol. Meas.* **24** 367-381  
5  
6  
7  
8 Panerai RB, Eames PJ & Potter JF 2006 Multiple coherence of cerebral blood flow velocity in humans  
9 *Am. J. Physiol. Heart Circ. Physiol.* **291** H251-H259  
10  
11  
12 Panerai RB, Kerins V, Fan L, Yeoman PM, Hope T & Evans DH 2004 Association between dynamic  
13 cerebral autoregulation and mortality in severe head injury *Br. J. Neurosurg.* **18** 471-479  
14  
15  
16 Panerai RB, White RP, Markus HS & Evans DH 1998 Grading of cerebral dynamic autoregulation from  
17 spontaneous fluctuations in arterial blood pressure *Stroke* **29** 2341-2346  
18  
19  
20  
21 Paulson OB, Strandgaard S & Edvinson L 1990 Cerebral autoregulation *Cerebrovasc. Brain Metabol.*  
22 *Rev.* **2** 161-192  
23  
24  
25 Ramos EG, Simpson DM, Panerai RB, Nadal J, Lopes JMA & Evans DH 2006 Objective selection of  
26 signals for assessment of cerebral blood flow autoregulation in neonates *Physiol. Meas.* **27**  
27 35-49  
28  
29  
30 Salinet ASM, Panerai RB & Robinson TG 2014 The longitudinal evolution of cerebral blood flow  
31 regulation after acute ischaemic stroke. *Cerebrovasc. Dis. Extra* **4** 186-197  
32  
33  
34 Simpson DM, Panerai RB, Ramos EG, Lopes JMA, Marinatto MNV, Nadal J & Evans DH 2004 Assessing  
35 blood flow control through a bootstrap method *IEEE Trans. Biomed. Eng.* **51** 1284-1286  
36  
37  
38 Smirl JD, Hoffman K, Tzeng YC, Hansen AE & Ainslie PN 2015 Methodological comparison of active-  
39 and passive-driven oscillations in blood pressure: implications for the assessment of cerebral  
40 pressure-flow relationships *J. Applied Physiol.* **119** 487-501  
41  
42  
43  
44 Subudhi AW, Panerai RB & Roach RC 2010 Effects of hypobaric hypoxia on cerebral autoregulation  
45 *Stroke* **41** 641-646  
46  
47  
48  
49 Tiecks FP, Lam AM, Aaslid R & Newell DW 1995 Comparison of static and dynamic cerebral  
50 autoregulation measurements *Stroke* **26** 1014-1019  
51  
52  
53 Van Veen TR, Panerai RB, Haeri S, Singh J, Adusumalli JA, Zeeman GG & Belfort MA 2015 Cerebral  
54 autoregulation in different hypertensive disorders of pregnancy *Am. J. Obstet. Gynecol.* **212**  
55 513.e511-517  
56  
57 Wang SY & Tang MX 2004 Exact confidence interval for magnitude-squared coherence estimates  
58 *IEEE Sig. Proc. Lett.* **11** 326-329  
59  
60



1  
2  
3 Welch PD 1967 The use of the Fast Fourier Transform for the estimation of power spectra: a method  
4 based on time averaging over short, modified periodograms *IEEE Trans. Audio Electroacoust.*  
5 **15** 70-73  
6  
7

8  
9 Zhang R, Zuckerman JH, Giller CA & Levine BD 1998 Transfer function analysis of dynamic cerebral  
10 autoregulation in humans *Am. J. Physiol. Heart Circ. Physiol.* **274** H233-H241  
11  
12  
13  
14  
15  
16  
17  
18  
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