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Observing temperature fluctuations in humans using infrared imaging

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Abstract

In this work we demonstrate that functional infrared imaging is capable of detecting low frequency temperature fluctuations in intact human skin and revealing spatial, temporal, spectral, and time-frequency based differences among three tissue classes: microvasculature, large sub-cutaneous veins, and the remaining surrounding tissue of the forearm. We found that large veins have stronger contractility in the range of 0.005-0.06 Hz compared to the other two tissue classes. Wavelet phase coherence and power spectrum correlation analysis show that microvasculature and skin areas without vessels visible by IR have high phase coherence in the lowest three frequency ranges (0.005-0.0095 Hz, 0.0095-0.02 Hz, and 0.02-0.06 Hz), whereas large veins oscillate independently.

Keywords

thermoregulation; skin microvasculature; infrared imaging; low frequency oscillation; wavelet phase coherence

1. Introduction

Recently, there has been a growing appreciation of using the microcirculation as a marker for cardiovascular health and as a means to assess the risk of cardiovascular events, stimulating interest in further development of instruments to detect and monitor basic vascular phenomena. Various noninvasive imaging methods to assess circulation have been developed, including laser Doppler and laser speckle imaging, brachial artery imaging, and fMRI (functional magnetic resonance imaging). Spontaneous, low-frequency fluctuations of signals recorded by these devices during baseline measurement have been recognized for a long time, but have been considered previously to be “drift” or “noise” that contaminate faster, higher energy signals. Bandrivsky et al. (Bandrivsky *et al.*, 2004) showed that frequencies as low as 0.005 Hz are involved in blood flow regulation, and more recently, Bernjak et al. (Bernjak *et al.*, 2008) showed that differences in low frequency fluctuations of blood flow among congestive heart failure patients relative to those of healthy controls may be of diagnostic value. They suggested that changes in these oscillations might be useful in testing drug efficacy (Bernjak *et al.*, 2008). Although laser Doppler has demonstrated that six distinct low frequency bands are attributable to various biological sources (Kvandal *et*

al., 2006), our main attention has been directed to the three lowest frequencies, which are those believed to be associated with vasoregulation of microvasculature. These frequency ranges are 0.005-0.0095 Hz, 0.0095-0.02 Hz, and 0.02-0.06 Hz, and are related to endothelium-derived hyperpolarizing factor (EDHF), rate of endothelial release of nitric oxide, and sympathetic activity, respectively (Kvandal *et al.*, 2006).

Previously, high frequency temperature oscillations related to the cardiac pulse were shown intraoperatively using infrared (IR) imaging of the exposed brain (Gorbach *et al.*, 2003). In the current study, we demonstrate that IR imaging is capable of detecting low frequency temperature fluctuations in intact human skin. The camera used is sensitive to IR photons emitted from living tissue during natural IR radiation. Blood at core temperature is warmer than the exposed surface, which has been cooled by evaporative losses, radiant losses, and conductive losses to ambient air. Therefore, blood flow, which carries thermal energy from the core to the surface, can be used as a natural contrast agent for IR imaging to assess tissue vasculature, including microvascular perfusion, vasomotion, and reactivity. The IR imaging method described here has a msec-response time and does not have the thermal inertia associated with thermocouples. The skin attenuates the energy of IR photons emitted from deeper structures and, as heat fluctuations propagate, their amplitudes decay as an exponential function of frequency. Consequently, only the described low-frequency temperature fluctuations can be measured readily on the skin surface.

We have identified temporal, spectral, and time-frequency differences at rest among microvasculature (MV), large sub-cutaneous veins (LCV), and skin areas without IR-detectable vessels (simplified as TWVV, i.e., tissue without visible vessels), that we were able to classify retrospectively using an image of the forearm as it underwent reactive hyperemia. The following describes the experimental design, image processing, and frequency analysis methods, as well as the characteristic differences in temperature fluctuation behavior among the three tissue classes.

2. Infrared Imaging

A calibrated IR camera (Santa Barbara Focalplane Array, Lockheed Martin, USA) with 0.015°C temperature sensitivity (3.0 - 5.0 μm wavelength, 320×256 pixels per image, 14 bits) was positioned directly above the dorsal aspect of a volunteer's forearm at a distance of ~90 cm. The forearm was secured gently with Velcro straps to reduce motion, and IR images were collected at a rate of 2 Hz during the following times: 10-min of baseline (BL), 5-min of occlusion of the upper arm with a blood pressure cuff inflated suprasystolically, and 10-min of post-occlusion (PO). The collected image set (~3000 images), with the z-axis representing time, provided the capability to extract a time series for each pixel ($\mathbf{p}_i$), approximately 82000 total time series (320×256 pixels).

3. Image Processing and Analysis

3.1. Image Alignment

Image alignment was conducted to reduce motion artifacts, using built-in functions of the Statistical Parametric Mapping Toolbox (<http://www.fil.ion.ucl.ac.uk/spm/>) of MATLAB 7.6 (MathWorks, Inc., USA). The first image served as a reference to align the remaining images by smoothing and re-sampling, followed by a rigid-body transformation (Frackowiak *et al.*, 1997). After alignment the average misalignment of the forearm was less than one pixel.

3.2. ROI Classification in Spatial Domain

A large object mask of the forearm was drawn manually drawn using ENVI 4.3 (ITT Industries, Boulder, CO) to exclude the background. Within this ROI, we were interested in separating MV and LCV from the TWVV to delineate temperature fluctuations of each tissue class.

During BL period, IR was unable to distinguish microvasculature (MV) from surrounding tissue, as they were both in local thermal equilibrium. During the PO period fresh, warm blood rapidly rewarmed the microvasculature by convection, but was slower to rewarm surrounding tissue (which occurs by conduction). Consequently, contrast was apparent between the warm microvasculature and cooler surrounding tissue, which led to dynamic heterogeneity in the IR images. To identify the peak of this heterogeneity, we calculated the co-occurrence matrix correlation (Gonzalez and Woods, 2002), r_{CM} , for each masked image of the image set, where a lower r_{CM} indicated greater heterogeneity. Images of the

maximum and minimum r_{CM} , $I_{r_{CM}}^{\max}$ and $I_{r_{CM}}^{\min}$, were isolated from the entire image set and were used to amplify the skin microvascular network relative to surrounding tissue and large veins as follows:

- MV was enhanced by subtracting the image of least heterogeneity from the image of most heterogeneity, and the result was called $I_{r_{CM}}^{\min-\max}$.
- MV was further enhanced by subtracting a blurred image of $I_{r_{CM}}^{\min-\max}$ from itself resulting in an enhanced image, I_H . The blurred image was generated by using an approximately circular-shaped averaging filter with a 7-pixel radius. Subtracting the average local temperature isolated the areas that were different, and therefore further enhanced the MV.

The enhanced image was used to automatically generate an ROI of microvasculature. By implementing the ‘water drain’ approach devised by Vainer et al. (Vainer and Moskalev, 2008), the rate of increase in the cross sectional area of each local spot was monitored. The level that corresponded to the largest rate of increase was set as the local threshold to determine the entire hyperemic spot, under the assumption that each individual spot had a 2D Gaussian distribution. To initialize the method, a 9×9 symmetric Gaussian low pass filter with $\sigma = 0.9$, based on the average diameter of MV spots, was fit to each spot to determine its center. The value of σ was set to best fit the size of the spots appearing in this image set. As the Gaussian low pass filter passed through the enhanced image, I_H , the correlation between the filter and the overlapped area was calculated, and the pixels with high correlations (>0.5) were considered as the centers of the spots. If a spot had multiple pixel centers, an average location of the centers was used.

LCV were separated from the negative values of the pixels in the MV-enhanced image, $-I_H$, by manual thresholding. As LCV are generally warmer and have a larger magnitude of recovery from occlusion than surrounding tissue, the first enhancement step darkened LCV

more than other tissue, because they were closer to pre-occlusion temperature in $I_{r_{CM}}^{\min}$. The negative values in the enhanced image highlighted LCV, and ROIs were generated by isolating pixels above an intensity threshold. The ROI for TWVV was identified by subtraction of the MV and LCV ROIs from the whole forearm ROI.

3.3. ROI Classification in the Temporal Domain

Each ROI was further sub-classified to identify regions with different temporal responses within the tissue class during BL period. There were three stages in the process. The first

was to reduce the temporal complexities, the second was to estimate the number of subclasses required to represent each tissue ROI, and the third was to perform clustering to identify tissues within each class that have similar temporal behavior.

First, temperature profiles for each pixel were obtained and smoothed to remove undesirable external signals, such as breathing, electronic noise, or ambient temperature fluctuations. Smoothing was performed using a 2nd order Savitzky-Golay filter with a 5 s time window to retain frequencies below 0.2 Hz, the normal breathing frequency at rest.

Second, the Signal Subspace Estimation (SSE) method (Dias and Nascimento, 2005) was used. It was designed to estimate the minimum number of bases required to construct the signal subspace in an n-dimensional space. In our application, this n-dimensional space consisted of pixels belonging to a certain tissue class. Its dimensionality, n , was estimated to be around 1200, which was the number of images collected during the baseline period. The signal subspace was spanned by its bases, which were the eigenvectors of the temporal correlation matrix $\mathbf{R}_T$. $\mathbf{R}_T$ was defined by $E[\mathbf{p}\mathbf{p}^T]$, the ensemble average of the autocorrelation matrix $\mathbf{p}\mathbf{p}^T$. SSE gradually increases the number of bases in the order of their corresponding eigenvalues and evaluates the set of bases by a defined cost function of mean squared error. The basis number that minimizes the cost function was assumed to be the number of required sub-classes. The benefit of using SSE is its insensitivity to the length of the signal and to the number of input pixels. Such insensitivity results from the eigen-decomposition and the designated cost function. More detailed explanations of SSE theory and design rationale can be found in (Dias and Nascimento, 2005).

Finally, given the SSE-estimated number of classes, local ROIs were clustered by the K-means algorithm (MacQueen, 1967) to minimize the within-class variation. Although Euclidean Distance (ED) is frequently used in clustering by measuring the distance between a data point and a cluster kernel, we found Short Time Series (STS) distance (Möller-Levet *et al.*, 2003) provides a more reasonable cluster result that maintains the spatial relationship and fits within our prior knowledge of anatomy. Given two time series collected under a fixed time interval t and extracted from pixels $\mathbf{p}_1 = [p_{11} p_{12} \dots p_{1n}]$ and $\mathbf{p}_2 = [p_{21} p_{22} \dots p_{2n}]$, the STS distance can be expressed as:

$$\text{STS}(\mathbf{p}_1, \mathbf{p}_2) = \sqrt{\sum_{i=1}^n \left[\frac{(p_{1(i+1)} - p_{1i}) - (p_{2(i+1)} - p_{2i})}{t} \right]^2} \quad [1]$$

The largest cluster on the forearm was chosen for further frequency analysis, as it provided the greatest statistical power to observe differences among the three tissue classes.

4. Frequency analysis

Frequency analysis of the three ROIs was performed by the following:

- During the baseline period, very low frequency oscillations (below 0.005 Hz) were removed from the raw data by an elliptical high pass filter (Aboy *et al.*, 2002) with a cutoff frequency of 0.004 Hz. The spectra of the p_i were derived from Fast Fourier Transform (FFT) with a 1024-point window. Given N as the number of pixels in the cluster, the averaged power spectrum $\bar{\mathbf{P}}_f$ was calculated by

$$\bar{\mathbf{P}}_f = \sum_{i=1}^N |FFT(\mathbf{p}_i)|^2 / N. \quad [2]$$

- Wavelet analysis (Torrence and Compo, 1998) was performed to estimate the duration of the dominant frequencies observed in the FFT result. The continuous Morlet wavelet transform was applied to the detrended data for each pixel, and then the spectra of the pixels were averaged via an operation similar to Eq. [2].
- In the spectrogram, different frequencies correspond to wavelet functions of different window length. For lower frequencies, wider window lengths are required to calculate the frequency response. A region called the Cone of Influence (COI) (Torrence and Compo, 1998) marks the areas at the beginning and the end of the signal where the window length exceeds the number of points, causing mathematical errors that can significantly impact results. After excluding such regions, four masks were generated to capture wavelet coefficients of 0.005-0.0095 Hz, 0.0095-0.02 Hz, 0.02-0.06 Hz, and 0.06-0.2 Hz, denoted as freq. 1, 2, 3, and 4, during baseline period.
- For quantitative assessment of the magnitude of oscillations in freq. 1-4, the average power in each frequency range was calculated from the wavelet power spectrum. Power across each frequency band was weighted by the corresponding wavelet function window length to avoid an overestimation of the average power. More details are given in (Torrence and Compo, 1998). The mean and standard error within each tissue type were calculated by treating each pixel as a separate sample.
- To estimate the degree of correlation between oscillators belonging to different tissue types, two computational approaches were implemented: time-averaged wavelet phase coherence (Bandrivsky *et al.*, 2004) and wavelet power spectrum correlation. The second approach was achieved by calculating the Pearson correlation between two wavelet power spectrograms for each frequency. Both can be expressed as a function of frequency. The COI region at each frequency scale was excluded during the calculation of coherence and correlation.

5. Results

IR images of the forearm were collected from a 50 year old, healthy female. Endothelial function and arterial stiffness were assessed by peripheral arterial tonometry (ENDOPAT, Itamar Inc., Israel) and showed no abnormalities.

Figure 1a shows a baseline IR image with clearly visible LCV. Figure 1b shows the temporal profiles of the same, single, pixel chosen from raw and aligned imaging sets. The raw profile (blue line) contains motion, resulting in artifactual temperature fluctuations that are particularly evident upon cuff inflation at 10.5 min. The aligned profile shows much less motion noise and reveals temperature oscillations (within the 10 minute baseline) that were previously eclipsed by misalignment.

Using the procedures mentioned in section 2, Figure 2a shows the average temperature of the whole forearm and the corresponding heterogeneity index, r_{CM} . The cuff-induced occlusion (shaded area, Fig. 2a) reduced mean forearm temperature, whereas reperfusion induced a rapid temperature increase. Figure 2b is the frame with the lowest r_{CM} corresponding to the frame of the greatest heterogeneity. Heterogeneity increases immediately during the post occlusion (PO) period, peaking approximately 30 s after cuff

deflation. As surrounding tissue conductively rewarms, heterogeneity returns to baseline levels, indicated by the microvasculature no longer being visible by IR.

Figures 3a-e show the results of spatial domain-based ROI classification. Compared to $I_{r_{CM}}^{\max}$ shown in Figure 3a, I_H shows enhanced microvasculature and reduced LCV intensity (Fig. 3b). From I_H , ROIs for MV, LCV, and TWVV were identified and are shown in Figures 3c-e, respectively, as bright areas.

Figures 4a-c are the classification maps derived from the K-means algorithm, which subclassifies the three ROIs by temporal characteristics, that were used to group pixels for further analysis. Different classes were represented by randomly assigned pseudo colors for visual recognition. The brightness of the colors is not related to any characteristics of the classes. The number of classes was estimated by SSE. The distance measure used in K-means was STS distance. Based on the assumption that local regions would behave similarly, we found that STS provided the best and least noisy classification, compared to maps generated using any of six other distance measures: Euclidean distance (ED); Spectral Angle Mapper (SAM) (Yudas *et al.*, 1992); Spectral Information Divergence (SID) (Chang, 2000); Dynamic Time Warping (DTW) distance (Liao, 2005); Pearson correlation r ; and Kendall's τ_b (Kendall, 1976). Figures 4(b, d, and f) represent the largest classes in Figures 4(a, c, and e).

The mean temperatures corresponding to ROIs in Figures 4d-f over the whole 25-min experiment are plotted in Figure 5. During the BL period (shaded area), the LCV were significantly warmer than other areas.

During the occlusion, all three tissue classes became cooler. TWVV was the coldest, probably because this tissue has the least local blood flow. LCV lost heat at the fastest rate and reached the same temperature as TWVV by the end of occlusion. The rates of temperature decline of MV and TWVV were not as fast as LCV. MV was the warmest of the three at the end of the occlusion period. During the PO period, the 3 areas had different levels of temperature recovery. LCV had the longest period (5 min) of increase and the largest magnitude change (0.54°C). The MV and TWVV had the same latency (<1 min), but the magnitude of increase of MV was larger (0.2°C). MV demonstrated the largest rate of increase (0.6°C/min) during hyperemia.

The temperature profiles for each pixel during the baseline period were analyzed by FFT. Power spectra of pixels in the same tissue ROI were averaged. Figure 6 shows two comparisons of tissue power spectra: (a) all three classes, and (b) MV vs. TWVV with error bars equal to standard error of each respective tissue class. Numbers 1 through 4 at the top of Figures 6a and 6b specify the four frequency ranges of interest (freq. 1-4). LCV had significantly stronger magnitude in 0.005-0.04 Hz than MV and TWVV (Fig. 6a). MV had greater power in frequencies 1-3 compared to TWVV (Fig. 6b).

While the LCV power spectrum had significantly greater magnitude than the other two tissue classes, the difference in the spectra of MV and TWVV was less pronounced. The most obvious difference was in freq. 2, where MV had three fold greater power. Additionally, the magnitudes of MV were also larger than TWVV in freq. 3. Differences in magnitudes of frequencies 0.06 Hz and higher were insignificant.

To exclude the abrupt decrease and increase in temperature caused by cuff inflation and deflation (Figure 5) from further analysis, wavelet spectrograms were generated for MV, LCV, and TWVV over the BL period (Figure 7a-c). The three plots in Figures 7a-c are displayed using the same contrast scale. Figure 7d illustrates the four time-frequency masks

for average power, coherence and correlation calculation, excluding the COI region that contains error.

Based on wavelet spectrograms the largest magnitude of oscillations in the four frequency ranges during baseline period originated in the LCV, followed in decreasing order by MV and TWVV. This also was confirmed by the average wavelet power calculation listed in Table 1. The significance of differences between the three tissue classes was checked by Mann-Whitney Rank sum test, and the p-values for freq. 1-4 were all less than 0.001. For MV and LCV spectrograms during the BL period, temperature oscillations that were related to sympathetic activity (Bernjak *et al.*, 2008) (freq. 3 range) varied in time and bandwidth (arrows in Figures 7a, b). The oscillation in freq. 2 range of Figure 7b also showed a similar pattern which appears at the 4th min and attenuated at the 6th min. Such phenomena cannot be seen from FFT analysis. In addition to showing the on/off nature of oscillations within freq. 3 range, the frequency of the oscillation increased over the baseline period. Interestingly, the time interval between oscillations marked by the arrows in MV was about 4 minutes (0.004 Hz), but was only 2 minutes (0.008 Hz) in LCV. This result suggested that LCV may be involved in blood flow regulation longer than MV. Low frequency oscillations in freq. ranges 1 and 2 may also exhibit similar characteristics, but the short duration of the baseline period did not provide sufficient data to observe this effect.

Following oscillation analysis, we examined correlations of MV, LCV, and TWVV in the time domain (Table 2). A high correlation was found between MV and TWVV, which reflected the similarity of the two temperature profiles over time. Figure 5 shows no visually discernable difference in fluctuation between them. Instead, some large fluctuations of LCV can be seen in the middle of the BL period. We suspect that these distinct fluctuations resulted in the lower correlation between LCV and the other two tissue types in Table 2.

Wavelet phase coherence and wavelet power spectrum correlation were calculated to investigate the pair-wise relationships between the three tissue classes in the frequency domain. Figure 8 shows the plots of power spectrum correlation (a) and time-averaged wavelet phase coherence (b) between tissue classes as functions of frequency. The x-axis is plotted in logarithmic scale. The average wavelet coherence and correlation between 30 white Gaussian noise simulations were calculated and plotted (black line in both plots). These simulations were not correlated with each other (Figure 8a), and provided the level of significance for the coherence analysis (Figure 8b). MV and TWVV showed high coherence over the majority of the frequencies except at lower than 0.008 Hz, around 0.01 Hz, and in the range of 0.02-0.03 Hz (Figure 8b, blue line). At least one dominant peak can be found in each frequency range (0.09 Hz, 0.015 Hz, 0.035 Hz, and 0.065 Hz), indicating that the phase of oscillations in MV and TWVV did not change with time. These results suggest that MV and TWVV may have shared oscillation sources or that they may have significant interactions that keep them tightly coordinated. LCV showed lower coherence with both MV and TWVV, reaffirming previous results in Table 1 and indicating that LCV may have different sources of oscillations.

Figure 8a shows several high power spectrum correlations that were not found in the phase coherence in Figure 8b, such as “LCV vs. TWVV” in freq. 1 and 3, and “MV vs. LCV” in freq. 1-3. It is noteworthy that the lowest coherence between MV and TWVV was at 0.02 Hz (Figure 8b), which means that at 0.02 Hz their phases were as uncorrelated as those of two white Gaussian noise signals. However, such low coherence has a strong negative correlation (<-0.5) in Figure 8a. It seems the timing of *on* and *off* at 0.02 Hz was reciprocal between MV and TWVV, and could be considered as another type of interaction. Another strong negative correlation happens in the lowest frequency around 0.0071 Hz. Since the

averaged coherence of white noise was getting higher in low frequencies, we cannot assign or hypothesize any physiological meaning to the corresponding negative correlation.

6. Discussion and Conclusion

Using IR imaging for vascular assessment provides several immediate advantages. Image sets can be collected passively and assessed rapidly, and no contact is necessary -which prevents contamination or adverse mechanical effects on the tissue under interrogation. The camera, which captures the endogenous thermo-contrasted blood vessels versus cooler exposed skin, can be utilized to monitor vasculature territories, perfusion, vasomotion, and vascular reactivity. The skin acts as an insulator and blocks direct emission of IR photons from deep structures of the forearm. Therefore, only low frequency temperature fluctuations can be measured on the skin surface. In contrast, under intraoperative conditions the less insulated surface vessels allow observation of their contractility at higher frequencies, including those of the heart beat (Gorbach *et al.*, 2003).

Low frequency temperature fluctuations from the forearm of a healthy subject were studied here. By using an image with maximum heterogeneity as a reference, a workflow was designed to extract three regions of interest: microvasculature, large conduit veins, and tissue without IR-visible vessels. Due to the anatomical complexity and different temporal dynamics of the human body, the pixels in each of the regions were further divided into a variable number of subclasses to minimize the within-class variance. Using the largest subclass of the three regions, we showed pair-wise differences between three tissue types in terms of the temperature change over time (via temporal profiles), the magnitude of frequency response (via FFT), and coherency (via wavelet phase coherence and power spectrum correlation). In the time domain LCV were the warmest areas during the BL period, and had the fastest rate of decrease during occlusion. MV had the fastest recovery rate, but LCV had the largest magnitude of recovery during the PO period. From FFT analysis we learned that LCV had larger magnitudes than MV and TWVV in 0.005-0.06 Hz. The difference in magnitudes higher than 0.06 Hz was not discernable from the FFT power spectrum.

We observed multiple appearances and disappearances of oscillations in frequencies 2 and 3 from the wavelet spectrograms calculated for LCV and MV. The average power calculation for each frequency range confirmed that LCV had the largest magnitude of oscillation, followed by MV and TWVV. The existence of correlations in the time-frequency domain between three tissue types was investigated via wavelet phase coherence and power spectrum correlation analysis. We found the pair "MV vs. TWVV" had larger correlation than other pair of comparisons, and a dominant peak can be located in each of the four ranges. Our future studies will compare the subclasses within the tissue type, and verify our findings from more subjects to test the reproducibility.

The pilot data presented here suggest that testing peripheral vascular function with IR imaging is feasible. This is an important next step in development of IR-based non-invasive imaging technologies capable of locating and distinguishing functionally different periphery vascular beds. The oscillations described in this article can be monitored noninvasively using IR imaging and may provide clues to relationships between blood flow regulation and vasomotion within different vascular territories.

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Figure 1.

a) A pixel (cross hair) used to check the effectiveness of the alignment procedure, b) the corresponding temperature profiles before and after alignment.

Figure 2.

a) Thermal profile of whole forearm ROI (thick solid line) and r_{CM} (thin dotted line), b) IR image corresponding to the minimal r_{CM} (maximal heterogeneity).

Figure 3.

a) IR images of the masked image excluding background pixels with a temperature scale in Celsius; b) enhanced microvasculature (I_H); c) MV extracted using water drain approach; d) LCV extracted from $-I_H$ by manual thresholding; and e) TWVV calculated as whole arm ROI less the MV and LCV ROIs.

Figure 4. ROI maps of: a) 7 classes via K-Means clustering; b) the largest cluster in (a); c) 10 classes via K-Means clustering; d) the largest cluster in (c); e) 14 classes via K-Means clustering; and f) the largest cluster in (e). (A color version of these images is available online.)

Figure 5. Mean temperature profiles of MV (from Fig. 4b), LCV (from Fig. 4d), and TWVV (from Fig. 4f) over the 25-min experiment, with the BL period shaded.

Figure 6. Power spectrum of: a) three tissue classes, and b) MV v.s. TWVV in 4 frequency ranges: 0.005-0.0095 Hz, 0.0095-0.02 Hz, 0.02-0.06 Hz, 0.06-0.16 Hz.

Figure 7.

Wavelet spectrogram of (a) MV, (b) LCV, and (c) TWVV during BL. (d) The four frequency masks are drawn; these were used to calculate the wavelet average power, phase coherence and power spectrum correlation between (a-c). The edges of the cone of influence (COI) at the beginning and end of spectrograms are delineated by the black line. The Y-axis is in log scale.

Figure 8.

Plots of: a) wavelet power spectrum correlation, and b) time-averaged wavelet phase coherence calculated for the three pairs of comparison: MV vs. TWVV, LCV vs. TWVV, and MV vs. LCV. Frequency (x-axis) is in log scale.

Table 1
The mean $\pm$ standard error of the average power of three tissue types in four frequency ranges. The unit of average wavelet power is AU²

Average power	Freq. 1	Freq. 2	Freq. 3	Freq. 4
MV	4.732 $\pm$ 1.630	3.525 $\pm$ 1.052	3.726 $\pm$ 0.995	2.960 $\pm$ 0.399
LCV	11.747 $\pm$ 3.197	18.041 $\pm$ 4.603	8.453 $\pm$ 1.212	4.907 $\pm$ 0.514
TWVV	2.751 $\pm$ 0.822	2.349 $\pm$ 0.345	2.586 $\pm$ 0.206	2.363 $\pm$ 0.188

Table 2
Correlations of temperature profiles of the three tissue classes during baselineperiod (see Figure 5)

	MV	LCV	TWVV
MV	1	0.5914	0.9989
LCV		1	0.5993