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A Novel Method for Extracting Respiration Rate and Relative Tidal Volume from Infrared Thermography

Gregory F. Lewis, BA¹, Rodolfo G. Gatto, MD, PhD¹, and Stephen W. Porges, PhD¹

¹Brain-Body Center, Department Of Psychiatry, University of Illinois at Chicago, Chicago, Illinois, USA

Abstract

In psychophysiological research, measurement of respiration has been dependent on transducers having direct contact with the participant. The current study provides empirical data demonstrating that a noncontact technology, infrared video thermography, can accurately estimate breathing rate and relative tidal volume across a range of breathing patterns. Video tracking algorithms were applied to frame-by-frame thermal images of the face to extract time series of nostril temperature and to generate breath-by-breath measures of respiration rate and relative tidal volume. The thermal indices of respiration were contrasted with criterion measures collected with inductance plethysmography. The strong correlations observed between the technologies demonstrate the potential use of facial video thermography as a noncontact technology to monitor respiration.

Keywords

respiration; facial thermography; infrared video

Introduction

Psychophysiological research relies on measurement of observable features such as behaviors and physiological signals, which both reflect and are modulated by the psychological state of the organism (i.e. response to an experimental stimulus). Respiration is a salient physiological signal that responds to behavioral, emotional, and cognitive challenges. Respiratory parameters of rate and depth have been measured in psychophysiological research conducted in several areas including deception (Thackray, 1968), stress (Grossman, 1983), emotion expression (Levenson, 1992; Philippot, 2002), hyperventilation syndrome and anxiety disorders (Han, 1997), biofeedback (Meuret, 2001), asthma (Lehrer, 1996), and cognitive load (Bell, 2004).

Respiration is commonly monitored in medicine, exercise physiology, and psychophysiology with transducers that make direct contact with the body. Typically these transducers involve measuring chest wall movements (e.g., strain gauges, pressure transducers, impedance measures) or nasal airflow (e.g., thermistors, spirometers).

Several psychological disorders, including anxiety disorders and depression, are characterized by abnormal respiratory activity. For example, individuals who panicked

Corresponding Author: Stephen W. Porges, Department of Psychiatry (MC912), 1601 W Taylor Street, Chicago, IL 60608, USA, sporges@psych.uic.edu, phone: 312-355-1557.

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respond to increased CO₂ concentration by increasing respiratory rate, while individuals who did not panic respond by increasing tidal volume (Papp, 1997). In other situations, individual changes in respiration provide diagnostic information. For example, both respiratory rate and depth increase in the seconds preceding an episode of sleep bruxism (teeth grinding behavior), breathing becomes faster and deeper and the frequency of these episodes is related to changes in depth of breathing (Khouri, 2008). Metabolic demands, such as workload increases during exercise, also induce changes in respiratory rate and tidal volume (Houtveen, 2002). Cognitive challenges similarly result in changes in respiratory cycle length and depth of breathing in the absence of physical activity (Myrtek & Spital, 1986; Gallego, 1996). Psychophysiological detection of deception (i.e. lie detection by a polygraph) incorporates several physiological signals that respond to deceptive answers to distinguish “guilty” and “innocent” subjects. Features of respiration, related to the depth and duration of individual respiratory cycles, contribute to the statistical model determining “guilt” or “innocence” in this setting (Barland & Raskin, 1975; Patrick & Iacono, 1991).

There are situations when direct contact measures of respiration are not possible or when direct measures will influence the participant’s response. Currently, there is interest in noncontact monitoring from the medical community to screen for illness and from the intelligence/security community to monitor psychophysiological reactivity during security screening. However, the ability to monitor subjects without their awareness and without inhibiting their range of behaviors has the potential to open up new lines of research and expand existing studies into more natural settings. Video infrared (IR) thermography is a promising technology for developing these noncontact measures. However, before IR thermography can be employed in field applications, the new noncontact measures need to be validated against existing techniques.

IR thermography measures the segment of light near the red color in the visible band. Specifically, it is defined as the portion of the electromagnetic spectrum in the region from 750 to 30,000 nanometers. The IR spectrum is typically divided into three sub-bands: the reflective band (750 to 3,000nm), thermal band (3,000 to 14,000nm) and extreme (14,000 to 30,000nm) band. Commercial video IR thermography cameras measure infrared signals in the 3,000 to 5,000nm wavelength range. Video IR monitoring of physiological processes introduces a new set of challenges for the psychophysiologicalist: movement artifact, depth of field impact on image focus, and environmental thermal noise contamination. The application of video IR thermography is a relatively new method to monitor physiological activity. Video IR thermography monitors dynamic thermal activity emitted from specific areas of living organisms and has been applied to monitor physiological signals from various species including insects (Kovac, Stabentheiner, Hetz, Petz, & Crailsheim, 2007), reptiles, (Borrell, LaDuc, & Dudley, 2005), humans (Fei & Pavlidis, 2006; Murthy & Pavlidis, 2006; Fei & Pavlidis, 2007; Pavlidis, Dowdall, Sun, Puri, Fei, & Garbey, 2007; Murthy, van Jaarsveld, Fei, & Pavlidis, 2009), and other mammals (Colak, Polat, Okumus, Kaya, Yanmax, & Hayirli, 2008). The passive nature of the IR technology results in a biosensor with minimal biohazard in contrast to other optical methods, such as spectroscopy, which may irradiate the target tissue with coherent light.

Recent research has explored the use of IR thermography in measuring respiration. Fei and Pavlidis (2007) used a coalitional tracking algorithm and wavelet decomposition to quantify temperature changes in the nostril. They used video thermography as a “virtual” thermistor and demonstrated that the thermal energy approximated the information obtained with a thermistor placed near a nostril.

Pavlidis and Murthy employed a two-step method to quantify respiration rate from video thermography (Murthy & Pavlidis, 2006; Pavlidis et al., 2007). They recorded temperature

in front of the face, with a profile view of the subjects head, in a climate controlled environment. First, they employed a training phase to develop a bimodal model of temperature distributions during inspiration and expiration. Second, a testing phase verified the model by classifying respiratory activity in new thermal images, with validation by the thermistor signal. Murthy et al. (2009) further demonstrated the clinical feasibility of video infrared thermography for vital sign assessment by detecting apneas in a sleep study.

Although these findings confirmed that breathing rate could be extracted from video IR thermography, the inference regarding other parameters of respiration was limited due to the use of a thermistor as the criterion technique. Thermistor measurements of breathing, as currently applied in psychophysiological research, do not generate an optimal criterion signal. The commercially available thermistors are not capable of providing a measure of tidal volume linearly related to criterion measures. Some of these limitations are due to the inherent physics of most commercial thermistors, which due to long time constants may not track breathing rate accurately across a wide range of breathing frequencies. Other limitations are due to the placement of the thermistor and are related to the physics of nasal airflow, the potential confounds of movement, and the possible influences of ambient temperature dynamics.

The current study was conducted to evaluate an alternative and more parsimonious noncontact strategy to monitor respiration rate and relative tidal volume based on thermal video of the face. In this study a facial tracking model is applied as an automated method to measure temperature changes within and around the nostrils. The thermal signal is transformed to quantify the duration and relative depth of each breath cycle. Functionally, inspiration brings in external air that cools the nostrils and expiration brings warm air from the body core to the nostrils. In previous research, measures of thermal changes from the nostrils have been used to monitor respiration rate with thermistors (Lindemann, Leiacker, Rettinger, & Keck, 2002) or IR video (Murthy & Pavlidis, 2006; Fei & Pavlidis, 2006; Fei & Pavlidis, 2007; Pavlidis et al., 2007; Murthy et al., 2009). We propose to extend these findings by demonstrating that accurate measures of respiration rate and relative tidal volume (i.e., highly correlated with calibrated measures of tidal volume) may be extracted on a breath-by-breath basis from thermal time series generated by video thermography focusing on the nostrils. In addition, the study addresses the limitations of previous studies by contrasting measures of respiration rate and relative tidal volume derived from thermography with a criterion volume measure derived from inductance plethysmography (i.e., LifeShirt®, Vivometrics, Inc., Ventura, CA).

Methods

Infrared video of the face was recorded during a variety of breathing protocols and analyzed off-line. A dynamic algorithm was developed to extract breath-to-breath timing intervals and relative tidal volume from thermal videos of the nostril region. The algorithm initially calculated an estimate of the dominant breathing rate, which was then used to create parameters to identify and to extract the breath-by-breath measures.

Participants

Twenty-five participants between the ages of 18 and 30 were recruited from the UIC community. The protocol was approved by the UIC Institutional Review Board. Data from 6 participants were used to refine the protocol. Data from the remaining 19 participants are described in this manuscript. Twelve participants were tested with a TVS- 700 thermal camera (Indigo System Inc, Goleta, CA) and seven participants were tested with a SC-6000 thermal camera (FLIR Inc, Santa Barbara, CA). The TVS-700 group was 67% White and 33% Non-White. The SC-6000 group was 43% White and 57% Non-White.

Procedures

Participants were fitted with the LifeShirt® system and remained seated throughout the recording in a comfortable chair. The imaging system was secured at ground level and pointed upwards towards (i.e., approximately 45°) the participant's face. Data were collected during three two-minute breathing conditions, while the participants were instructed to breathe: 1) spontaneous, 2) slow and deep, and 3) rapid and shallow. To evaluate the influence of IR camera sensitivity on the analysis, data were collected with two imaging systems (TVS-700, SC-6000). To synchronize the thermal video with the LifeShirt®, an IR light emitting diode mounted on the shirt of the participant was illuminated to produce a temporal marker in the thermal video when an event marker was inserted in the data stream from the LifeShirt®.

All data were collected in the same room within a sealed building where temperature and humidity are controlled throughout the year. Room temperatures fluctuated within a limited range of approximately 70-72 °F. Vents were left open in the recording room and air was continuously flowing into the room during the recordings.

Thermal cameras

The TVS-700 monitors thermal signals with wavelengths between 8,000 and 14,000 nanometers. The TVS-700 has a 320×240 pixel resolution and a sensitivity of 0.08C °. The TVS-700 was set to the highest sampling rate, a rate that varied across time with a maximum of approximately 29 frames per second. A second set of data was collected with the SC-6000. The SC-6000 monitors thermal signals within the same bandwidth as the TVS-700. However, the SC-6000 has superior pixel resolution (640 × 510) and enhanced sensitivity (0.02° C). Moreover, the SC-6000 has programmable sampling rate, which was fixed at 30 frames per second. Initial data extraction was conducted with commercial software (Thermovision v1.0 and Researcher v2.8, FLIR Inc, Santa Barbara, CA).

LifeShirt®

Respiratory parameters were sampled at 50 Hz from the LifeShirt®. The LifeShirt® is an inductance plethysmograph vest embedded with Respibands (a sinusoidal arrangement of electrical wires that are excited through a low AC current) at the level of the ribcage and the abdomen. The stretching of the vest during breathing changes in the inductance of both Respibands. Respiratory inductance plethysmography is an accepted standard for unobtrusive respiratory monitoring used in clinical and research settings (Wilhelm, Roth, and Sacker, 2003).

VivoLogic® software (Vivometrics, Inc.) uses the output of the Respibands to derive a dynamic measure of relative tidal volume. The LifeShirt® can be calibrated to generate an accurate estimate of tidal volume by calculating the chest movement during a breath constrained to a fixed air volume. Calibration of the LifeShirt® tidal volume signal permits VivoLogic® to adjust the relative contributions of the abdominal and thoracic strain gauge signals to the tidal volume signal across the range of potential subject body positions. To address the potential limitations of using an uncalibrated measure of tidal volume, calibrated and uncalibrated measures of tidal volumes were contrasted from data previously collected with the LifeShirt®. This previously collected data set included calibration by breathing into a fixed volume bag (800 mL) and measured respiratory parameters during an ambulatory task. These estimates of calibrated tidal volume were highly correlated with estimates derived from the data after removing the VivoLogic® calibration¹.

In the current protocol subjects maintained a single posture (sitting). Within this restricted setting, it was assumed that the relative contributions of the thoracic and abdominal strain

gauge signals would be constant. Thus, the selection of ambulatory subjects for comparison is a worst-case scenario for comparing relative tidal volume from calibrated and uncalibrated respiratory data. In the current study, thermal estimates of relative tidal volume were linearly transformed to match the slope of LifeShirt® derived measures of relative tidal volume.

Tracking model

Thermal features of respiration were extracted from each nostril. However, even in a laboratory setting with compliant seated subjects, the location of the nostrils within the frame was constantly changing. Video tracking algorithms were used to compensate for head movements and to automate the extraction of the thermal signals. We chose a tracking system that could (1) function in real-time, (2) perform post-hoc analysis of thermal video, and (3) identify features of the nose in three dimensions.

A tracking algorithm developed by Tao and Huang (1998), based on the Piecewise Bézier Volume Deformation model (PBVD), was applied. The PBVD algorithm was designed to track the movement of specific facial features (Tao & Huang, 2002). The PBVD model consists of a collection of 3D Bézier volumes in which the face mesh model is completely embedded. These Bézier volumes are defined by two layers of small, non-parallel polygons which lie above and below the face mesh model. A coarse-to-fine strategy was used to achieve robust tracking and to reduce the computational complexity. Image pyramids were constructed from each input video frame. The motion parameters were estimated at the coarse level first and then refined at higher resolution. The first video frame was used to manually initialize the face model and a confidence measure was introduced to monitor the tracking quality (Tao & Huang, 1999).

Each planar facet of the model is defined by four vertices in 3D space. Each vertex that is visible in the frame also corresponds to a 2D pixel coordinate within the frame. Software was designed to allow an operator to select the vertices that encircle each nostril region of interest (ROI). This was achieved through a graphic user interface, coded in MATLAB (2007a, The MathWorks, MA, USA). The influence of head movements, which can obscure the ROIs, was reduced. Pilot testing suggested that pointing the camera at an upward angle of approximately 45° towards the face of the seated participant improved the initialization of the PBVD model. Tracking did not fail when the camera was in this position.

A thermal signal was extracted from each infrared thermal video by the tracking program via the following steps. First, the initial frame from the thermal video recording is displayed and the 2D coordinates from all vertices in the 3D PBVD model initialization are superimposed on the image as blue dots (see Figure 1). Second, once this is displayed, the operator with the use of a pointer tool can freely zoom into any section of the image and select the vertex points that completely define the ROI. In the current study, the vertex points that enclose the nostril were selected (see Figure 2). Once the ROI is defined, an updated 3D model is generated for each video frame with the pixel coordinates of each selected vertex defining the smallest convex polygon that contains all of the selected points. Operationally, this polygon is the ROI for each video frame.

Since the ROI size, shape, and location vary within boundaries imposed by the PBVD model, the operator can visually verify the ROI placement by reviewing an animation that superimposes the ROIs on the video and by viewing the mean temperature output for each

¹Empirically, the covariation of calibrated with raw uncalibrated signals for 8 ambulatory subjects was evaluated. Tidal volume was quantified using the same method applied in this study (i.e., peak-to-trough) for both the calibrated and uncalibrated signals. The breath-to-breath correlations ranged from .83-1.0 with a mean correlation of .92.

ROI (see Figure 3). The thermal signal exported from the tracking program has the native sampling rate of the thermal video, which differed between the thermal cameras and between the cameras the criterion measures of respiration. Thermal signals in this study were based on the average of two mean temperatures, one for each nostril ROI.

Data Reduction

TVS-700 videos were processed to extract time stamps (GORATEC, Germany). To synchronize the thermal and criterion signals, thermal signals from the variable frame rate system were initially upsampled to 30 Hz by a sample-and-hold procedure and then downsampled to 5 Hz by linear interpolation. The 5 Hz sampling rate was chosen to ensure that TVS-700 derived signals represented measured information as opposed to interpolated information. Although the ideal frame rate of the TVS-700 was near 30Hz, the time between individual frames fluctuates considerably. Adjacent timestamps were as much as 200 ms apart in some cases, and we chose to downsample the entire signal to this rate to minimize the impact of these periodic delays in signal acquisition. Additionally, breath intervals were extracted from thermal signals recorded on the SC-6000 at their native 30 Hz rate. The tidal volume signal from the LifeShirt® was reduced by linear interpolation from its native 50 Hz rate to 5 Hz for the TVS-700 analyses and to 30Hz for the SC-6000 analyses.

The tidal volume signal from the LifeShirt® IP was recorded continuously throughout the experiment. Thermal videos were recorded during each of three breathing protocols (rapid and shallow, slow and deep, and spontaneous). The respiratory component of the thermal signal was isolated via a three-step filtering procedure. First, the dominant breathing rate (BR) for the recording was estimated by spectral analysis of the raw thermal signals. Second, the thermal signal was transformed to a volume correlate by integration. Third, the integrated time-series was high-pass filtered to reduce the influence of noise. The breath interval (BI) and relative tidal volume (RTV) of each breath were then calculated. Extracted variables from the transformed thermal signal and the tidal volume signal from the LifeShirt® were compared within and across the three respiratory conditions.

Step 1: Dominant Breathing Rate (BR)—Thermal and LifeShirt® volume time series were linearly detrended and zero-padded to a length of 1024 samples. A 1024-point fast Fourier transform (FFT) was used to calculate the spectral density distribution. This spectrum was stabilized by convolution with a 9-point Parzen window.

Within an expanded range (due to the variations in breathing frequencies across the three conditions) of 3 to 65 cycles per minute (cpm), the frequency with the greatest spectral density was selected as the Breathing Rate (BR). Analyses of variance identified significant differences among the three breathing conditions for both the TVS-700 and SC-6000 groups (all $p < .05$) and confirmed participant compliance with the breathing instructions. The mean BR (SD) for the TVS-700 group was 41.38 (9.98) cpm in the rapid and shallow condition, 15.08 (3.67) cpm in the spontaneous condition, and 10.02 (4.98) cpm in the slow and deep condition. For the SC-6000 group, the BR was 47.17 (15.20) cpm in the rapid and shallow condition, 19.94 (8.88) cpm in the spontaneous condition, and 13.28 (5.45) cpm in the slow and deep condition. Correlations were calculated between BR measures derived from the LifeShirt® and thermal signals (see Table 1).

Step 2: Integration—The thermal signal was transformed to generate a measure proportional to changing lung volume. Mean nostril temperature is proportional to air flow. The coldest temperature observed was operationally defined as the peak of inspiration, and the warmest temperature is observed was operationally defined as the nadir of expiration. Thus, integration of the thermal time series generated a transformed time-series, which

contained a component assumed to be linearly related to tidal volume. However, the integrated signal also contained variance due to thermal noise in the environment, particularly slower temperature variations due to circulating air.

Step 3: Dynamic Filtering—To remove sources of variance in the thermal time series unrelated to the respiratory signal, the integrated data were processed with a cubic polynomial filter. A cubic-polynomial filter was designed for each thermal signal with a cutoff frequency, f_c , below the BR. High-pass filtering isolated the respiratory signal in the integrated thermal series. A scaling factor, α was employed to maintain a fixed distance between the BR and the filter cut-off frequency. The dynamics of the filter were determined by the BR. This procedure is similar to that described by Porges and Bohrer (see Porges, 1985; Porges & Bohrer, 1990).

$$f_c = \alpha * BR; \text{ where } \alpha = 0.385.$$

The filter length (L) varied as a function of the cut-off frequency and sampling rate. Operationally, filter length determined the cut-off frequency of the filter. Filter length was rounded to the nearest integer value.

$$L = \text{ROUND}(f_s/f_c); \text{ where } f_s \text{ is the sampling rate in Hz.}$$

The cubic polynomial filter of length L was convolved with the integrated thermal series to create a template of the low frequency trend in the signal. The trend series was then subtracted from the integrated series. The high-passed difference series was trimmed by (L + 1)/2 samples at each end.

Breath-by-breath variable extraction

Local maxima and minima were identified in each time series. Relative tidal volume (RTV) was defined as the range of each oscillation. The smoothed first derivative of each signal was used to identify the peak of expiration. Breath interval (BI) was defined as the time between sequential expiratory peaks. Due to the filtering quantification procedures, the thermal time series was truncated resulting in fewer breaths in the time series. Each set of BI and RTV values (thermal and LifeShirt®) was aligned to the maximal cross-lagged correlation within 2 breath cycles in either direction using the built-in align signals function (Signal Processing Toolbox, MATLAB 2008).

Relative tidal volume transformation

In order to compare the accuracy of relative tidal volume estimates across subjects, each set of thermal RTV values was transformed to match the slope and mean of the corresponding LifeShirt® values. This linear transformation followed the least-squares method to calculate a slope, M, and offset, B, from the paired RTV values derived from the LifeShirt® and thermal signals.

Calculation of M and B—

$$M = \frac{\sum_{i=1,2,\dots,N} [RTV_{thermal,i} - \overline{RTV}_{thermal}] * [RTV_{LifeShirt,i} - \overline{RTV}_{LifeShirt}]}{\sum_{i=1,2,\dots,N} [RTV_{thermal,i} - \overline{RTV}_{thermal}]^2}$$

$$B = \overline{RTV}_{LifeShirt} - M * \overline{RTV}_{thermal}$$

Linear Transformation of $RTV_{thermal}$ —

$$RTV_{lin} = M * RTV_{therm} + B$$

Since both the thermal and LifeShirt® tidal volume measures exhibited heteroscedasticity (i.e. variance at large values was greater than variance at small values), both RTV measures were log transformed for presentation (see Figure 7) and calculation of within-subject correlations (see Table 2).

Bland-Altman Plots

Bland-Altman plots were generated for BI estimates from the LifeShirt® and each thermal imaging system. The plot illustrates the difference between the two measures as a function of the mean of the two measures (Bland & Altman, 1986). The confidence region of the Bland-Altman plot defines the ± 2 SD range within which 95% of the differences lie.

Results

The application of face tracking to the data extraction was successful within the constraint that the subject's face remained in view of the IR camera. When the face was in view of the IR camera, the program was able to identify the ROI coordinates throughout the recording. However, for one subject in each group, large or abrupt movements (either moving the head out of the field of view or rotating the face away from the camera) caused the program to fail.

All subjects participated in the three breathing conditions that defined the protocol. Data were excluded if either the thermal or LifeShirt® signal was corrupted. In the TVS-700 group, two participants were excluded from the shallow breathing condition. One participant failed to maintain rapid, shallow breathing for the full two minutes. The other participant abruptly shifted posture during the recording and distorted the LifeShirt® signal as well as the IR recording. In the TVS-700 group, no subject had data excluded from more than one condition.

In the SC-6000 group, three subjects were excluded from the shallow breathing condition due to failure of the LifeShirt® system. Facial tracking failed during the slow breathing condition in one participant, due to the face being obscured from the camera when the subject turned their head to speak to the researcher. In the SC-6000 group, one participant had valid data only during the spontaneous breathing condition. This subject was removed from analyses that were collapsed across conditions (see footnote, Table 2). Within subject correlations between the LifeShirt® derived RTV and the raw thermal estimates of RTV were calculated without log transformation to provide a conservative estimate of the covariation between the two RTV measures.

Correlations between the dominant breathing rates (BR), calculated via spectral analyses (see Step 1 in Data Reduction), extracted from thermal and LifeShirt® systems approached unity in all conditions with both cameras (see Table 1).

As described above, BI and RTV were extracted from the thermal and LifeShirt® signals for each respiratory cycle. Correlations were calculated to evaluate the linear relationship between the variables derived from the thermal and LifeShirt® system. Limitations on the range (i.e., different breathing conditions) and precision of the measurements (i.e., different cameras) reduced the within condition correlations. Across the full range of respiratory activity, within subject correlations between the two sets of extracted variables (thermal and LifeShirt®) approached unity (see Table 2). Correlations within each respiratory condition

were lower and quite variable, since some subjects attempted to fix breathing (rate and volume) despite no instruction to do so, while others did not.

One weakness in using correlations to compare two measurement systems is that the values are not independent (Bland & Altman, 1986). A common method to address this weakness is to provide a scatter plot of measurement differences versus mean measurement values. Visual inspection of these plots will reveal bias, for instance if the differences are positive for small values and negative for large values. This type of plot was proposed by Bland and Altman (1986) and is commonly referred to as a Bland-Altman plot. Bland-Altman plots have been used to evaluate the accuracy of different technologies used to monitor heart rate (e.g., Heilman & Porges, 2007). In Figure 4, Bland-Altman plots for breath intervals from each thermal imaging system revealed a 95% confidence region of $\{-0.62, 0.69\}$ seconds for the TVS-700 and $\{-0.39, 0.40\}$ seconds for the SC-6000 when run at 30 Hz. Visual inspection of the Bland-Altman plots indicates that overestimation and underestimation of BI were equally likely to occur for both thermal imaging systems across the full range of BI. On average, both IR systems demonstrated very small mean differences between the two sets of BI, indicating that the intervals in each series summed to approximately the same duration. For the TVS-700, the average difference was approximately 36 msec. For the SC-6000, which sampled data at the faster rate of 30 Hz, the average difference was approximately 6 msec.

Breath-by-breath parameters from two participants, one with each thermal imaging system, are demonstrated in the following figures. Note the clusters in Figure 5B, representing each respiratory condition. With increased sampling frequency, the precision to detect smaller changes in breath-to-breath durations is improved. Associated with this increased sampling frequency are higher correlations between the thermal and LifeShirt® systems, especially during conditions of fast breathing when fewer data points define a respiratory cycle.

Thermal estimates of RTV were transformed to match the slope of the LifeShirt® estimates from the same condition. For each thermal imaging system, a set of RTV values was log transformed to generate a homoscedastic distribution of RTV pairs (thermal, LifeShirt®). The units of these measures of volume, although arbitrary, were monotonic (i.e. deeper breaths always generated larger values than shallower breaths for the same subject). We present two scatter plots of transformed RTV pairs (see Figure 7). Mean within-subject correlations between the LifeShirt® measure of RTV and both the raw and the log transformed thermal estimate of RTV are reported in Table 2.

Discussion

The current study was conducted to evaluate the use of video IR facial thermography as a valid noncontact technology to dynamically evaluate both respiration frequency and relative tidal volume. The study had four unique features. First, it focused on measures of both respiration frequency and relative tidal volume. Second, it applied a robust tracking algorithm that enables accurate extractions of the thermal activity in the area of both nostrils, even during head movements. Third, by using sensitive criterion measures of relative tidal volume and respiration frequency, the degree that thermal measures covaried with criterion contact measures could be evaluated. Fourth, it evaluated whether enhanced pixel resolution, sampling rate, and thermal sensitivity improved the statistical covariation between thermal and criterion signals.

By attending to the above features, the study provides the first documentation that an accurate measure of relative tidal volume can be obtained with infrared video thermography. In addition, consistent with the literature (Murthy & Pavlidis, 2006; Fei & Pavlidis, 2006;

Fei & Pavlidis, 2007; Pavlidis et al., 2007; Murthy et al., 2009), which used less direct measures of respiratory function (i.e., thermistor), we report a strong covariation between thermography and thoracic circumference measures of respiration frequency.

We used two research strategies to evaluate the covariation between the thermographic and criterion measures of respiration. First, we evaluated whether predominant breathing rate was similar in both criterion and thermal signals for each participant during each of the breathing conditions. Second, we evaluated breath-by-breath covariation between the thermal signal and criterion measures.

Spectral analysis was used to identify the predominant breathing rate in each signal. These data (see Table 1) illustrate the strong convergence between the methods with correlations approaching unity. Although these findings are encouraging, the real test for potential field applications would require the quantification of breath-by-breath measures of rate and relative tidal volume across a broad range of breathing parameters ranging from fast and shallow breathing to slow and deep breathing. Individual within subject correlations were calculated between the breath-by-breath thermal and criterion signals. When the correlations were calculated across a wide range of breathing (i.e., including all breath cycles completed during each of the three breathing conditions) measures of both breath interval and relative tidal volume approached unity (see Table 2). However, when the correlations were calculated within each homogeneous breathing condition, the correlations were noticeably lower. The findings illustrate the strong relation between thermal and criterion signals, when there is a reasonable breath-by-breath range in both frequency and tidal volume. Thus, the findings demonstrate that the relationship between the thermal and criterion signals are strongly linear. Moreover, the data demonstrate the effectiveness of our algorithm when applied across an expanded range of respiratory activity.

By using a facial tracking algorithm, we were able to reduce the restraints placed on the participants. The initial pioneering research, conducted by Pavlidis and his colleagues, collected thermal data without tracking algorithms in a tightly controlled physical environment. Our study demonstrated that sensitive thermal data can be collected without the constraint of a tightly regulated test chamber. Our quantification strategy enables the extraction of the respiratory parameters from the thermal signal, which may include potentially confounding influences on the infrared thermography from temperatures variations in the room and face movements. We achieve this by a three stage conditioning strategy, including dynamic high-pass filtering of the thermal signal to isolate the respiratory signal prior to the extraction of the individual cycle respiratory parameters. We recover the respiratory waveform with three processing steps: (1) estimation of respiration rate from raw thermal recorded in the ROIs (nostrils), (2) integration of the mean ROI time-series, and (3) filtering of the integrated series to extract the respiratory component. In this protocol, respiratory rate was relatively constant during each condition, and breathing rate was estimated from the entire recording. However, this algorithm could function during more heterogeneous breathing by dynamically adjusting the filter to match dynamically changing respiratory parameters.

To facilitate the extraction of the thermal signal from the ROIs (nostrils), we employ a tracking methodology that is different from the coalitional tracking previously reported (e.g., Fei & Pavlidis, 2007). Our method automated the placement of the ROIs in each frame of the recorded video. As tracking methods improve, they will result in an improved ability to extract an array of physiological variables from the face (e.g., respiration, heart rate, facial muscle activity) with fewer behavioral restraints (e.g., minimizing movement and maintaining orientation towards a single camera).

A notable limitation in generalizing our technology to the field was our dependence on using a different tracking model for each breathing condition. In the current protocol, this was an unavoidable consequence of our limited data storage capacity. Thermal videos could only be recorded in 2-3 minute segments (see Figure 4). As a result, the PBVD model had to be initialized each time data collection was initiated with the consequence of generating a unique distribution of vertex points for each breathing condition. In the current study this occurred at the start of each of the three conditions (rapid and shallow, spontaneous, slow and deep breathing).

Each time the model was initialized new vertex points defining the nostrils were selected by the operator. To minimize this within subject source of variance, the operator was instructed to select the smallest region that completely encloses each nostril. However, even following these rules, the distribution of the vertex points varied among the models. Thus, the area defined by the operator also varied (see Figures 1-3), since the distribution of the vertices in the PBVD model determines the size and shape of the ROI.

As illustrated in Figure 8, the black oval represents the right nostril of the same subject during two breathing conditions, shallow and spontaneous breathing, designated A and B. The polygon surrounding the nostril is the ROI selected by the operator for each of the two thermal videos. Respiration induces periodic cooling and heating in the nostril (black oval). The white area, within the ROI boundary, is skin and cartilage near the nostril region. Respiration induces a smaller change in skin surface temperature. Inspiratory air flow would reduce the mean ROI temperatures of both A and B. But, since the polygon in Figure 7B includes more pixels that are not coincident with the nostril, the magnitude of change would be dampened. Although this dampening effect does not influence the accuracy of the estimates of instantaneous respiration frequency, it will influence the estimates of relative tidal volume. Continuous recording of thermal data across breathing conditions would eliminate the discontinuities in the volume estimate that were created by our segmented recording.

ROI size and shape do not affect the extraction of breath interval estimates, but it does influence the measurement of relative tidal volume. This effect is apparent in Figure 6A. While the relationship between RTV estimated by thermography and the LifeShirt® is linear in all three conditions, the slope and intercept are visibly different between the shallow and spontaneous conditions. Under conditions of continuous recording, a single tracking model could be used to extract respiratory parameters even if breathing features were dynamically changing. In order to compare RTV estimates across all subjects and conditions, the linear adjustment described at the end of the Methods section was used to calculate RTV_{lin} .

Our study suffers from some of the same limitations as previous work in noncontact measurement. For example, although we applied tracking algorithms to deal with movement, the subjects were seated and instructed to minimize head movement to optimize exposure to the camera. These conditions are more similar to those encountered in a clinic, where a patient may be confined to a bed. However, there are situations in which covert surveillance of physiological state might be an objective. To reach this objective, the current technology would need to be augmented by using multiple thermal video systems with dynamically adjusting lenses that could track a moving target within a larger environment.

The methodology described in this paper could, with minor modifications, be applied in the field. By applying time series analysis to the raw thermal signal it would be possible to generate a real-time estimate of respiratory rate. The estimate of respiration rate would then modulate a second filtering stage with enhanced precision of detecting breath-to-breath estimates of respiration rate and relative tidal volume. This three-stage dynamic filtering

strategy would follow the methods presented in our study: parameter estimation, numerical integration, and signal conditioning. With a small delay and minimal processing power, the respiratory volume waveform could be recovered.

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Figure 2.
Operator selecting vertex points that define one nostril region of interest (ROI).

Figure 3. Operator reviewing the extracted waveforms and placement of the ROIs in the final frame of the recorded thermal video.

Figure 4.
Bland-Altman plot of BI differences at BI means.
A. LifeShirt® and TVS-700 BI, 5 Hz sampling rate.
B. LifeShirt® and SC-6000 BI, 30 Hz sampling rate.

Figure 5. Single subject, extracted variables from TVS-700 thermal camera and LifeShirt® system. A) Relative Tidal Volume, 5Hz signals. B) Breath Interval, 5Hz signals.

Figure 6.

Single subject, extracted variables from SC-6000 thermal camera and LifeShirt® system. A) Relative Tidal Volume, 5Hz signals. B) Breath Interval, 5Hz signals. C) Breath Interval, 30Hz signals.

Figure 7.

A. Relative Tidal Volume (All subjects, All conditions). TVS-700

B. Relative Tidal Volume (All subjects, All conditions). SC-6000

Figure 8.
Illustration of ROI placement for independent PBVD models.

Table 1

Correlation between thermal and mechanical breathing rates (BR)

Respiratory Condition	Thermal Imaging System	
	TVS-700	SC-6000
Shallow	0.996 (N = 10)	1.000 (N = 4)
Normal	0.941 (N = 12)	1.000 (N = 7)
Forced	1.000 (N = 12)	0.990 (N = 6)

Table 2

Mean (STD), within subject correlation between thermal and LifeShirt® extracted variables

Camera		Total
TVS-700	Breath Interval	0.98 (0.02)
	Relative Tidal Volume (raw)	0.90 (0.09)
	Ln (RTV _{lin})	0.96 (0.03)
SC-6000	Breath Interval	0.95 (0.05)
	Relative Tidal Volume (raw)	0.90 (0.07)
	Ln (RTV _{lin})	0.96 (0.03)

5 Hz reduced signals used for all calculations. N = 12, for the TVS-700 group and N = 6 for the SC-6000 group. All subjects with valid data in at least two conditions included.