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Contact-free physiological monitoring using a markerless optical system

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Abstract

Purpose—Physiological noise remains a major problem in MRI, particularly at higher imaging resolutions and field strengths. The aim of this work was to investigate the feasibility of using an MR-compatible in-bore camera system to perform contactless monitoring of cardiac and respiratory information during MRI of human subjects.

Methods—An MR-compatible camera was mounted on an 8-channel head coil. Video data of the skin was processed offline to derive cardiac and respiratory signals from the pixel signal intensity and from head motion in the patient head-foot direction. These signals were then compared to data acquired simultaneously from the pulse oximeter and the respiratory belt.

Results—The cardiac signal computed using the average image pixel intensity closely resembled the signal obtained using the pulse oximeter. Trigger intervals obtained from both systems matched to within 50 ms (one standard deviation). The respiratory signal computed from small in-plane movements closely matched the signal obtained from the respiratory belt. Simultaneous MR imaging did not appear to have an effect on the physiological signals acquired via the contact free monitoring system.

Conclusion—Contact-free monitoring of human subjects to obtain cardiac and respiratory information is feasible using a small camera and LED mounted on the head coil of an MRI scanner.

Keywords

pulse oximetry; peripheral gating; cardiac monitoring; respiratory monitoring; optical motion correction; in-bore cameras

INTRODUCTION

Signal fluctuations originating from physiological processes in the human body are often a source of artifacts in MRI. Cardiac motion, pulsatile blood flow, and CSF pulsations all present a challenge for artifact-free imaging. Similarly, respiratory motion is often detrimental, in particular in abdominal and cardiac MRI. Both cardiac and respiratory effects lead to potentially confounding physiological noise in functional magnetic resonance imaging (fMRI), which can be of comparable magnitude to the desired signal (1). This is

increasingly problematic as fMRI is performed at higher magnetic fields, since physiological noise increases with increasing signal strength (2,3) and reduces the SNR gains that might otherwise be achieved at higher fields. To mitigate these problems, measurements of a patient's cardiac and respiratory signals are often used in synchronization strategies, such as triggering and gating (4), or statistical signal separation techniques in the case of fMRI (1,5).

Cardiac motion, and the cardiac cycle in general, is often monitored using the electrocardiograph (ECG) signal; however, this requires the attachment of electrodes, and the signal is often corrupted by the scanner radiofrequency field, the imaging gradients, and motion of the electrodes in the main magnetic field. This is particularly problematic at field strengths above 3 T. A common alternative is a finger-mounted pulse oximeter (photoplethysmograph), which is an optical device that is not affected by the magnetic environment. However, a general disadvantage of pulse oximetry is that motion of the device can lead to false readings (6). Attaching the pulse oximeter to the patient adds to the technologist's workload and can lead to practical difficulties: for example, it is not uncommon for the pulse oximeter to become detached from the finger of the patient during the MRI examination.

Respiratory motion is often monitored using an air-filled belt (commonly called a 'respiratory belt' or 'respiratory bellows') attached to a pressure sensor. This technique has been used in MRI for over thirty years (7). Respiratory monitoring using a respiratory belt can allow free breathing during the scan, rather than requiring the patient to perform breath holding. Although breath holding can be effective for some patients during shorter scans, it is impractical in many patient populations and for longer scan sessions. Navigators are also commonly used to track the diaphragm position (8) or measure the field changes resulting from respiration (9), but these require MR pulse sequence modifications and can extend the scan time. Respiratory monitoring using a respiratory belt avoids these problems, but has the disadvantage that a device must be attached to the subject and must be individually adjusted in order to function reliably, which interrupts patients workflow and costs time.

Recently, there has been substantial work performed modifying and deploying camera hardware to function inside the MRI scanner bore, at field strengths from 1.5 T to 7 T (10–13). The main objective of this development work has been for prospective motion correction (14), where optical data is used to track a head-mounted marker and correct for head motion in real time. The use of in-bore cameras extends previous proof-of-concept work performed by Zaitsev et al. (15) using a stereo camera system outside the magnet to track head motion. In-bore cameras, however, have a major advantage in that line-of-sight to the patient is easier to achieve. Given the high cost of patient motion (16), and the apparent efficacy of optical prospective correction, it appears likely that in-bore cameras will become increasingly widely used.

Recent developments in health technology have shown that it is possible to remotely measure parameters such as pulse and respiration rate, using cameras. This is consistent with the scientific literature, where similar measurements have been demonstrated on numerous occasions (e.g. (17,18)). The goal of this study was to determine whether there is potential

for in-bore camera systems, normally used for motion correction, to obtain physiological data similar to that currently obtained using the pulse oximeter and respiratory monitor.

METHODS

Hardware

An updated version of an in-bore camera normally used for marker-based prospective motion correction (11,19) was adapted for this work. The camera was mounted above an 8-channel head coil, giving an unobstructed view of the subject's forehead (Fig. 1). In Ref. (11), an infrared light emitting diode (LED) ring was used; however, in this work a single white 5 mm LED (Nichia Corp., Japan) was placed beside the camera lens. This provided on-axis illumination of the skin in the visible part of the spectrum (LED color temperature: 5000 K).

In vivo experiments

Video data were collected from a volunteer ('Subject 1') placed at the isocenter of a 3 T MRI scanner (750w, GE Healthcare, Waukesha, WI, USA). The camera was operated at a frame rate of 30 Hz, with a resolution of 640×360 pixels and an exposure time of 33 ms. Monochrome video data were saved to file during the experiment. There were several reasons for using monochrome video, rather than color video. First, most optical adaptive systems, including ours, use monochrome data for tracking, and a software modification would be required to log video in color. Second, the literature indicates that the plethysmographic signal is the strongest in the green channel, but occurs simultaneously in all three color channels (17); therefore, combining the channels is a reasonable approach. Finally, combining color channels reduces data storage and processing requirements.

Data from the vendor-supplied pulse oximeter and respiratory belt were also acquired, at sample rates of 100 Hz and 25 Hz, respectively. Data were logged for a 90 s period, comprising three 30 s blocks: no MR imaging, imaging with a 3D sequence (fast spoiled gradient echo, TR: 7.3 ms, TE: min full, flip angle: 12 degrees), no MR imaging. Approximate synchronization was achieved manually by initiating logging simultaneously. Video data from a second volunteer ('Subject 2') were recorded in a later experiment during a diffusion-weighted MR acquisition. In this case, the camera orientation differed by 180 degrees from the first experiment, giving a different view of the subject's forehead.

A final experiment was performed on a third volunteer to compare the signal obtained from the video data with field changes in the brain originating from respiratory motion (as reported in Pfeuffer et al. (9)). For this purpose, an EPI time series comprising 200 single slice images was collected over a 60 s period (TR: 300 ms, TE: 50 ms, flip angle: 60 degrees, matrix size: 96 × 96, slice thickness: 5 mm). Raw data were saved to file to preserve the complex data for later analysis of the time-varying image phase.

Video processing

All video processing was performed offline in Matlab (MathWorks Inc., USA) after performing the in vivo experiments and removing the subjects from the scanner. The same

video stream was used to derive four separate signals for later comparison to the recorded signals from the pulse oximeter and respiratory belt (Fig. 2). Here, we denote these four signals as $c_{int}(t)$, $c_{mot}(t)$, $r_{int}(t)$, $r_{mot}(t)$, where c and r denote cardiac and respiratory information, respectively. The subscripts *int* and *mot* indicate that the signal is derived from pixel intensity changes and translational motion, respectively. The derivation and meaning of these signals is described in the following, with reference to Figs 2 and 3.

The video frames are initially cropped to a square of 360×360 pixels. This removes the head coil from the field of view periphery and results in a video showing a region of skin brightly illuminated in the center, but darker towards the edges. This natural fall-off in brightness makes windowing redundant, which otherwise would be required to reduce edge effects and improve robustness to bulk motion. The pixel intensity module in Fig. 2 sums all pixels over the entire (square) image for each frame to generate an N -by-1 vector, where N is the number of frames in the video.

The 1D motion module shown in Fig. 2 performs image registration using a sub-pixel implementation of the phase correlation method (Fig. 3). As in the pixel intensity module, each frame is initially cropped to a 360×360 square, removing the stationary head coil, which would otherwise be a confounding factor in the motion calculation. The first frame in the video sequence is used as a reference; each of following $N - 1$ frames in the video are compared to this reference to compute the relative displacement in the image x - and y -directions. This is achieved by applying the inverse FFT to both the reference and i th cropped frames and computing the phase difference in the Fourier domain. This phase difference is a 2D ramp with a gradient proportional to the displacement between the two frames. This gradient, and hence the displacement, is found using the sub-pixel phase correlation method, described in more detail in Ref. (20). The shift in the image x -direction (patient left-right) is discarded and only y_i , the shift in the image y -direction (patient head-feet) is used for further processing.

The cardiac filter module in Fig. 2 is a finite impulse response filter designed using a Kaiser-Bessel window to capture likely frequencies in the cardiac signal. The filter has a passband between 0.6 Hz and 10 Hz, stopbands below 0.5 Hz and above 12 Hz, and stopband attenuation of 30 dB. The respiratory filter module was designed in the same manner, but has a passband between 0.2 Hz and 0.6 Hz and stopbands below 0.1 Hz and above 0.7 Hz. Filtering is applied in a forward-backward manner to the data, which results in zero phase filter, i.e., without a time shift in the filter output (21). Applying the cardiac and respiratory filters to the pixel intensity signal, derived as described above, produces $c_{int}(t)$ and $r_{int}(t)$, respectively. Applying the cardiac and respiratory filters to the 1D motion signal gives $c_{mot}(t)$ and $r_{mot}(t)$, respectively.

Comparison and cardiac trigger detection

The two reference signals from the pulse oximeter and respiratory belt and the four video-derived signals ($c_{int}(t)$, $c_{mot}(t)$, $r_{int}(t)$, $r_{mot}(t)$) were all scaled to cover a total range of 1, in order to allow easy comparison between them. This is valid, since the scaling of all signals is already arbitrary, and they all simply provide relative magnitude. Since the SNR of the data appeared sufficiently high, no outlier detection or removal was performed.

To provide a better comparison of the potential usefulness of the cardiac signals for cardiac gating, a simple algorithm was applied in order to check for consistency of the time period between detected pulses (analogous to the RR interval in ECG). Trigger locations were found for each curve based on two parameters: a threshold, set arbitrarily to 0.6, and a minimum interval time, set here to be 300 ms. Trigger locations were then defined as any time point more than 300 ms since the previous trigger, where the signal crossed the 0.6 threshold and had positive gradient. These trigger locations were then used to calculate the trigger-trigger interval time.

Visualization

Previous work, unrelated to MRI, has shown that it is possible to augment video data to make subtle intensity changes visible to the naked eye (22). Using a similar method, we augmented the video data acquired for this work using the video-derived cardiac signal, $c_{int}(t)$, and the following algorithm. Rather than cropping the N video frames to a square and processing all pixels in that square together, frames are divided into m -by- n non-overlapping rectangular regions. Processing is applied to all pixels in each region separately to extract $c_{int}(t)$ for each m, n . This m -by- n -by- N signal is then resampled using bicubic interpolation to the original video resolution and used to generate a ‘modulation video’. The modulation video is superimposed onto the red channel of the otherwise grayscale images. Cardiac pulsation can then be easily seen as a red tone overlaid on the original video. Depending on the values selected for m and n , spatial discrimination can be traded for robustness and SNR of the signal.

RESULTS

Figure 4a shows a comparison of the reference data from the pulse oximeter, with video-derived signals $c_{int}(t)$ and $c_{mot}(t)$. A good match to the pulse oximeter data is apparent for $c_{int}(t)$ in terms of the timing and magnitude of peaks. The motion derived data, $c_{mot}(t)$, is clearly not robust enough for reliable triggering, but nonetheless does contain detail resembling the ballistocardiogram (which has been previously reported when using a tracking marker (12)). MR imaging was performed during the middle 30 s of data acquisition and appears to have no effect on any of the acquired physiological data.

Trigger locations, computed as described in the Methods section, match well between the reference pulse oximeter data and $c_{int}(t)$. Figure 4b shows a zoomed-in subset of trigger locations from the central 30 s period in Fig. 4a. Although synchronization between the two signals was not perfect in our setup, there is a clear one-to-one mapping between triggers derived from the two signals. That is, every trigger detected in the pulse oximeter data stream was also detected in $c_{int}(t)$, and there were no extra triggers detected in $c_{int}(t)$ that were not detected in the pulse oximeter signal. This one-to-one mapping makes it possible to compare the time interval between triggers (Fig. 4c): the difference between trigger intervals from the pulse oximeter and $c_{int}(t)$ has a mean of < 0.01 s and standard deviation of 0.05 s, meaning that most trigger intervals computed from the two signals are within 50 ms of each other.

Figure 5 compares respiratory data from the respiratory belt to the video-derived signals $r_{int}(t)$ and $r_{mot}(t)$. In this case, there is no evidence that the intensity based signal $r_{int}(t)$ correlates with breathing motion. However, motion based data, $r_{mot}(t)$, correlates strongly, although the shape of the signals differ in a number of aspects, such as the more consistent peak height in the respiratory belt signal. Again, MR imaging appears to have no effect on the acquired physiological data. Supporting Figure S1 compares 1D motion and filtered 1D motion data ($r_{mot}(t)$) to mean image phase from the EPI time series. Again, there is a strong correlation between the signals, although the EPI time series data appears to capture respiratory motion with superior SNR than the video-derived signal.

Based on the promising match between the pulse oximeter data and the signal from video pixel intensity, $c_{int}(t)$, several experiments were performed to achieve better spatial discrimination of this signal, as described in the Methods section. Figure 6a shows an example where the image has been divided into a 3-by-6 grid, giving a total of 18 sub-regions. The first 10 s of the resulting signal, $c_{int}(t)$, for each subregion is shown in Fig. 6b. For some regions the cardiac signal is particularly strong; for others (such as regions containing little skin), it is virtually non-existent.

Figure 7a shows sample frames from the video, enhanced using the results shown in Fig. 6. The full video is available in the supporting information. Some ‘leakage’ of enhancement occurs into regions where there should be none (e.g. headcoil, hair), due to the coarseness of the grid ($m = 3$, $n = 6$). However, the grid dimensions are freely adjustable, so spatial resolution can be traded for spatial averaging and signal quality. The same processing was applied to data from Subject 2 (Fig. 7b, and video in supporting information online).

DISCUSSION AND CONCLUSIONS

Our data indicate that it is possible to obtain similar information to the pulse oximeter and respiratory belt without physical contact to the subject. Finger-mounted pulse oximetry has existed since the 1930s (23) and the use of both the pulse oximeter and respiratory belt has been common in clinical MRI since its inception. Now, however, small in-bore cameras are becoming popular for prospective motion correction. It appears that the same camera hardware could potentially be used for physiological monitoring purposes, perhaps eliminating the need to use devices that physically contact the patient.

The rationale behind analyzing image intensity information is that it is well known that light absorption of the skin varies with the cardiac cycle. Our data confirm this and indicate that it is practical to obtain a useful signal in the MRI environment using existing hardware. The rationale behind using sub-pixel motion information comes from previous work in adaptive motion correction, where small movements (on the order of $100\ \mu\text{m}$) in the head-feet direction show cardiac and respiratory motion (12). This does seem to be the case here; however, in our implementation, detection of the ballistocardiogram was not as robust as detection of breathing motion. However, application of another algorithm, such as the method used by Balakrishnan et al. (24) (based on principle components analysis), may produce a good quality ballistocardiogram from motion information.

We have not thoroughly investigated the algorithm's robustness to large-scale bulk head motion. The maximum image displacement from the initial position was 16 pixels (approximately 3 mm) in the experiment reported in Figs 4 and 5, indicating that the subject remained relatively, but not perfectly, still during the experiment. Some motion robustness can therefore be assumed, but further experiments with different amounts of motion should be performed in future. Multiple cameras could perhaps be used in order to ensure that an acceptably large region of skin remains in the camera field of view at all times. Bulk motion sensitivity is a challenge shared by pulse oximetry, so our method is not necessarily inferior in this case, and a detailed comparison of the relative robustness of these methods should be the subject of future work.

Bulk head motion is likely to be more problematic for respiratory monitoring than cardiac monitoring, since much of the bulk motion will lie in the same frequency range as breathing and will not be removed by filtering. This may explain some of the differences between the curves in Figs 5 and S1. Another issue is that head motion in the head-feet is at best a proxy for chest motion. Figure S1 indicates that it may in fact be a poorer predictor of respiratory motion than MR image phase data. However, the camera could be positioned so as to view the abdomen directly: in this case, changes in reflected light from clothing may prove to be more useful than motion information. Alternatively, new developments in time-of-flight cameras may be more suitable for contactless detection of respiratory motion.

The camera used in this work contains a color CMOS sensor, but the color information was not used in the analysis, as most motion tracking software, including ours, uses monochrome image data. For this reason, most optical systems typically do not send color image information out of the MRI scanner. The white LED is clearly necessary for illumination, as previous attempts at photoplethysmography using ambient light (17) have been in a well-lit environment. We have not investigated the potential to use the infrared part of the spectrum. In any case, the LED used in this work is placed out of the field of view of the subject, so is not disturbingly bright.

The goal of this work was to test the feasibility of obtaining physiological data from within the scanner bore without physical contact to the subject. Real time processing and MRI scan synchronization was not attempted. This would make filtering more difficult and maximum acceptable computation times more restrictive, but these challenges are not insurmountable. However, even without real-time availability of the signal, the method may still find applicability for signal separation in fMRI or combined EEG-fMRI, as has been previously done using a marker-based tracking system (25). Although we have not attempted this here, using the video-derived cardiac signal in place of the pulse oximeter signal is a promising avenue for future work.

In conclusion, this study aimed to determine whether potential exists for in-bore optical tracking systems, normally used for adaptive motion correction, to obtain similar physiological data to the pulse oximeter and respiratory belt. The data shown here indicate that this is indeed the case.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Figure 1.

(a) Camera system mounted on the head coil, including a white light emitting diode (LED) for illumination. (b) A single frame from the captured video stream showing illuminated skin on the forehead of the subject.

Figure 2.

Processing applied to video data to obtain the four different signals for later comparison to the pulse oximeter and respiratory belt data: $c_{int}(t)$ and $c_{mot}(t)$, marked in red, contain cardiac information; $r_{int}(t)$ and $r_{mot}(t)$, marked in blue, contain respiratory information. The subscripts 'int' and 'mot' indicate that the signal is derived from pixel intensity information and from image motion information, respectively.

Figure 3.

Motion quantification algorithm applied within the 1D motion module in Fig. 2. Only motion in the video image y-direction (y_i) is used in later processing; motion in the video image x-direction (x_i) is discarded. The image y-direction corresponds to the scanner z-direction, or the patient head-feet direction.

Figure 4.

(a) A comparison of Subject 1's cardiac signal obtained from the pulse oximeter (top) with the signal derived from the video pixel intensity ($c_{int}(t)$, middle) and from the one-dimension motion of the subject ($c_{mot}(t)$, bottom). (b) Results of a simple cardiac trigger detection algorithm applied to the top two plots in (a), shown for the central 30 s, during simultaneous MRI imaging. (c) A comparison of the time interval between triggers in (b) for the entire 90 s experiment.

Figure 5.

A comparison between the signal obtained from the respiratory belt (top) with that derived from video pixel intensity ($r_{int}(t)$, middle) and one-dimension motion in the head-feet direction ($r_{mot}(t)$, bottom). These data were acquired simultaneously with the cardiac data shown in Fig. 4.

Figure 6.

(a) Division of each video frame into m rows and n columns, forming $m \times n$ sub-regions. (b) a plot of signals $c_{int}(t)$ for each on the 18 sub-regions in this example. Some sub-regions show a strong cardiac signal; others do not.

Figure 7.

Example frames from the enhanced videos showing cardiac signal visualization for Subject 1 (left) and Subject 2 (right). The full videos are available in the supporting information.