Decoupling of Respiratory Motion with Wavelet and Principal Component Analysis

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Abstract. The establishment of patient specific models for minimal access surgical simulation requires the acquisition and co-registration of 2D endoscope/laparoscope video with 3D tomographic data with matched physiological status. The advent of *in vivo* catheter tip tracking devices offers the potential for improving the robustness and accuracy of current registration techniques in the presence of tissue deformation. For bronchoscope simulation, reliable extraction of respiratory motion allows retrospective gating of the acquired tracking data so that video bronchoscope views can be grouped according to different respiratory phases. In practice, the motion data recorded is coupled with patient and respiratory motion and the decoupling of the two is not trivial. This paper presents a novel motion decoupling technique for simplifying 2D/3D registration under the influence of normal respiratory motion. Wavelet analysis has been used to identify and remove episodes due to coughing and extreme breathing patterns. The technique has been validated with data acquired from 8 subjects, demonstrating the practical value of the proposed method.

1 Introduction

Minimal invasive surgery is increasingly being used in routine clinical practice as it significantly reduces patient trauma and recovery time. The technique, however, requires a high degree of manual dexterity and hand-eye coordination. The use of simulation devices has been proven to be an economical and time saving tool for acquiring, as well as assessing basic surgical skills. With the current systems, however, the lack of visual realism and tactile feedback represents major challenges to minimal invasive surgery tasks. To this end, computer simulation is becoming an important tool for acquiring, as well as assessing, basic surgical skills. In our previous study, we have developed a reliable 2D/3D registration technique, which incorporates structural matching, and inter-frame coherence for providing photorealistic rendering for bronchoscope simulation [1]. The method has shown great promise in establishing the camera pose during bronchoscope examination such that matched surface details can be extracted to augment the virtual bronchoscope views. The technique, however, assumes that there is no large tissue deformation between 3D tomographic data and 2D bronchoscope video. To simplify the 2D/3D registration process and accommodate general tissue deformation during examination, the use of catheter tip EM tracker provides a practical way forward. In a catheter tip tracking enabled bronchoscopy examination, a 6 DoF tracker is required to monitor the global position and orientation of the patient. This allows the cancellation of global motion, thus facilitating the localisation of the bronchoscope in relation to the CT scan volume. One of the issues involved in tracking the pose of bronchoscope camera is its movement due to respiratory motion. The trajectory acquired needs to be separated into different phases of the respiratory cycle such that the corresponding bronchoscope views can be co-registered with 3D tomographic data. Since during bronchoscope examination, both patient and respiratory motion affect the reading of the catheter tip, they need to be decoupled before further processing steps can be applied. The purpose of this paper is to provide a novel respiratory motion decomposition scheme to accurately monitor the respiratory cycle in the presence of large patient motion and filter out episodes due to coughing and extreme breath patterns.

2 Methods

2.1 Experimental Setup

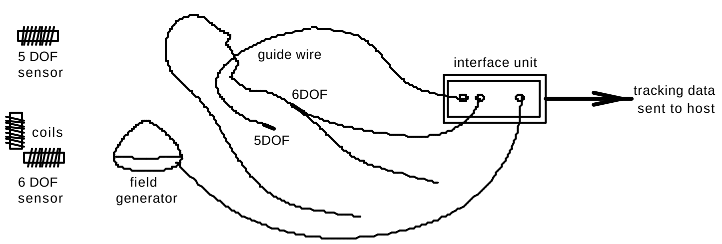

Fig 1: The basic configuration of using Aurora electromagnetic tracking systems in a clinical setting for removing global patient motion and recovering respiratory pattern.

The basic system layout is shown in Fig 1 where an Aurora (Northern Digital, Ontario, Canada) EM tracking system is used. The system provides both 5 DoF catheter tip and 6 DoF (MagTrax Reference) EM trackers. Additional positional trackers

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can be introduced to extract respiratory motion so that video bronchoscope views can be grouped according to different respiratory phases. The introduction of extra tracking devices, however, complicates the experimental procedure and may not be practical in clinical examinations. Due to the different frequency characteristics of the respiratory and global motion, it is possible to simultaneously acquire and decouple these motions by using a single sensor positioned on the chest wall. The decoupling of global and respiratory motion in this case, however, is not trivial as they are intertwined depending on the projection axes. Given the fact that the dominant cyclic variation of the signal is due to respiratory motion which has a constant principal direction of variation during a given time window, principal vector decomposition is used to extract the plane of respiratory motion over time, independent of global motion. To account for coughing and other extreme respiratory motions, wavelet analysis [2] was applied to detect and isolate these rapid motion episodes. In this paper, we present a new technique that uses principal component analysis based method to retrieve "hidden" respiratory patterns from position sensors in different axes and wavelet transform to filter out coughing and extreme breath patterns.

2.2 Decoupling of Respiratory Motion

Given that the dominant variation of the signal is due to respiratory motion and it has a constant direction during a given time window, then principal component analysis can be employed to decouple it. The principal vector is expected to lie on the same plane over time and, thus projecting the signal on this plane can isolate the signal variations due to respiration. We define as f the positional vector over time of the MagTrax reference sensor attached to the chest. Typically the respiratory pattern has a higher frequency than positional drift of the patient, a kernel box $d(t)$ is convolved to each axis of the motion sensor such that

$$\mathrm{f}^*(t) = f(t) - f(t) * d(t) \tag{1}$$

In discrete form, the samples over time can be represented as:

$$\mathrm{f}^*(t - w\cdot\Delta t),\quad \mathrm{f}^*(t - w\cdot\Delta t + \Delta t),\quad \ldots\quad \mathrm{f}^*(t + w\cdot\Delta t) \tag{2}$$

A matrix h is defined for each time sample as:

$$h(t) = \left[\mathrm{f}^*(t - w\cdot\Delta t),\quad \mathrm{f}^*(t - w\cdot\Delta t + \Delta t),\quad \ldots\quad \mathrm{f}^*(t + w\cdot\Delta t)\right]^T \tag{3}$$

h has dimension of $(2w+1)\cdot 3$, where 2w has a typical length of 30 sec. Therefore, the covariance matrix is produced as:

$$M(t) = \left(h(t) - \bar{h}(t)\right)\cdot\left(h(t) - \bar{h}(t)\right)^T \tag{4}$$

The principal vector $p(t)$ is estimated from the eigen decomposition of the covariance matrix. Finally, r is a scalar vector, which represents the decoupled respiratory motion. This is estimated as the projection of $\boldsymbol{f}^*$ on the principal vector.

$$r(t) = \mathrm{f}^*(t)\cdot p(t) \tag{5}$$

2.3 Wavelet Analysis

During bronchoscope examination, coughing involves major distortion to the airway. In order to identify these episodes wavelet analysis was used [2,3,4]. Wavelet analysis provides localised frequency analysis and has the potential to analyse signals that contain multiple non-stationary or transitory signal characteristics. Their main advantages are both its ability to perform local analysis and to preserve time information.

Let $y(t)$ be a function in the Hilbert space $L^2(R)$ of measurable, square-integrable one-dimensional functions with an average of zero, and denote $y_{2^j}(t) = 2^{-j} y(t/2^j)$. The wavelet transform of a function $f(t)$ at the scale 2^j and position t is given by the convolution product:

$$W_{2^j} f(t) = f * y_{2^j}(t) \tag{6}$$

The *dyadic wavelet transform* is the sequence of functions $\left(W_{2^j} f(t)\right)_{j\in Z}$, where Z represents the set of integers. In multiscale edge analysis, $y(t)$ is usually chosen to be the derivative of some smoothing function and, thus, the local maxima of $\left|W_{2^j} f(t)\right|$ indicate the positions where sharp signal variations occur. In order to identify these variations we define an energy function e with threshold x.

$$e(t) = \sum_{j<10} W_{2^j} f(t) > x \tag{7}$$

3 Validation

Eight subjects were recruited for this study with their respiration monitored by an Aurora (Northern Digital, Ontario, Canada) 6 DoF EM tracker positioned on the sternum. Their respiration was monitored for about two minutes. Global motion was introduced to the couch on which subjects were seated to simulate the sensor reading coupled with two types of motion. During the experiment the relative position of the subject and the couch was fixed and the subjects were allowed to have extreme respiratory movements including coughing. An additional EM tracker was placed on the base of the couch so that its relative movement to that of the sensor located on the subject's chest wall provided reference readings purely due to respiration. This information was then used to validate the accuracy of the motion decoupling results based on the single sensor method. The results of this study also demonstrate that episodes related to coughing can be reliably identified and filtered out. The subject was asked to cough at a particular time, while slight global motion was introduced. An example is demonstrated in Fig 3 and has been used to validate the wavelet technique.

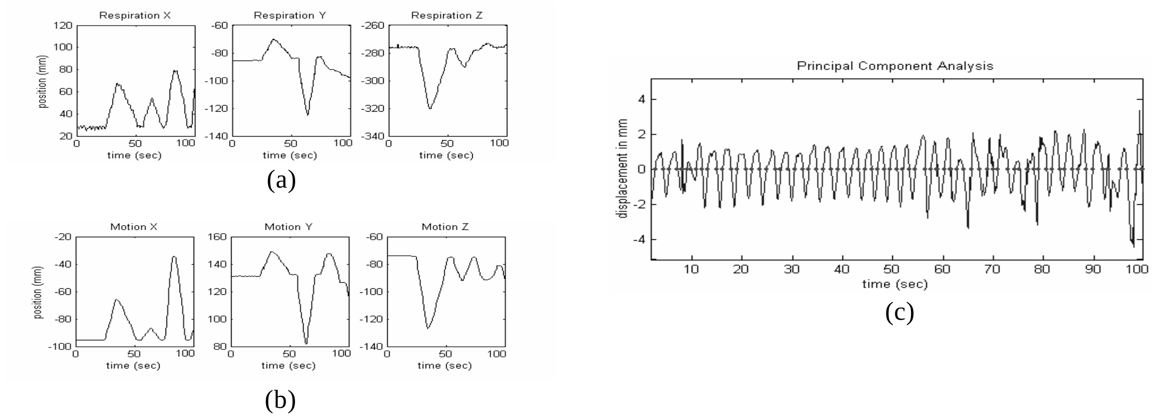


Fig 2: Example position traces sampled by the EM tracker and the extracted respiratory motion pattern. (a) *x, y, z* positional component of the data received from the EM tracker attached on the chest of one of the subjects, (b) *x, y, z* positional component of the data received from the EM tracker attached on the couch, (c) The recovered respiratory component.

4 Results

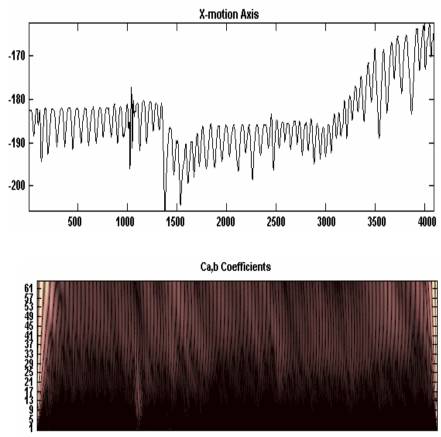
Fig 2 demonstrates typical results derived from the proposed respiratory motion decoupling technique. It illustrates the *x, y, z* positional component of the data received from the EM tracker attached on the chest of one of the subjects (a), as well as the *x, y, z* positional component of the data received from the EM tracker attached to the base of the couch, (b). Fig 2(c) represents the recovered respiratory component after applying the proposed technique described in section 2.1 to the data received from the EM tracker on the subject's chest. In order to validate our technique the correlation between the recovered waveform (section 1.1) and the waveform estimated by applying principal component analysis to the vector between the two EM tracker tool tips has been calculated for eight subjects. Table 1 outlines the correlation accuracy of the results derived from the 8 subjects studied, which achieved an overall accuracy of 82.7%. This indicates the ability of the technique in extracting the respiratory signal in spite of the fact that it is not apparent in the initial EM tracking data due to global motion. Fig 3 demonstrates the wavelet analysis of the X, Y and Z positional data that have been acquired from an EM tracker attached on the skin of a healthy subject. The wavelet coefficients are plotted for each signal component. Fig 3(d) represents the energy function of the X-wavelet coefficient graph that has been defined within equation (7). The time interval where the patient coughs shows up clearly as a peak that corresponds to 88 sec. By using the wavelet decomposition scheme, extreme breathing patterns can be reliably identified.

Subjects	1	2	3	4	5	6	7	8
Correlation	0.918	0.962	0.805	0.794	0.879	0.791	0.786	0.687

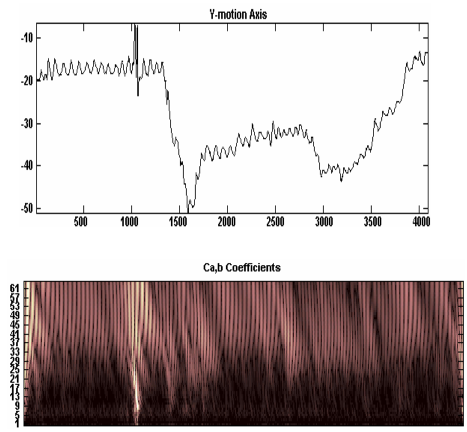
Table 1: Correlation of the waveform estimated by the suggested respiratory decoupling motion technique with the waveform estimated by relative position of two sensors.

5 Discussion and Conclusions

In conclusion, we have presented a novel method of decoupling respiratory motion from the signal received from an EM tracker attached to the chest. We used wavelet analysis to filter out episodes due to coughing and other extreme breathing patterns. Principal component analysis has been employed to decompose the respiratory cycle from global motion. It should be noted that the basic assumption used for respiratory motion decoupling is that the global positional drift has a relatively low frequency in comparison to respiratory cycles. When there is sudden motion involving large acceleration, it is likely that rapid changes in sensor readings will be introduced, in this case, the algorithm based on principal component analysis will lead to detection errors. Since we have used wavelet analysis to sense rapid sensor movement, these events will also be isolated along with coughing and extreme respiratory motion. The results in this study indicate that the respiratory motion component can be reliably extracted. Even though the respiratory signal has non-zero components in all *x-y-z* axes and it is blended with global motion, they can be reliably decoupled with the proposed technique. Furthermore, episodes related to coughing can be detected easily and filtered out using wavelet analysis, which is appropriate for detecting localised signal variations. The technique developed can facilitate a 2D/3D registration regime under deformation and increase the accuracy of the registration process.



a)



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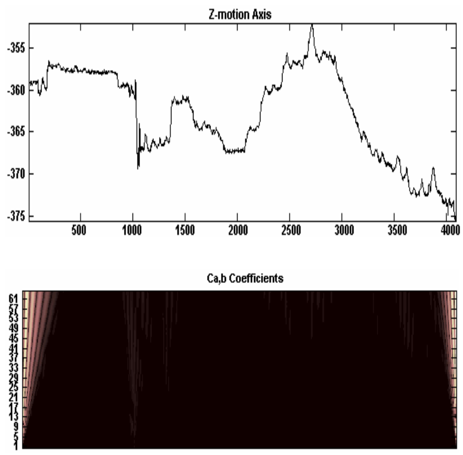
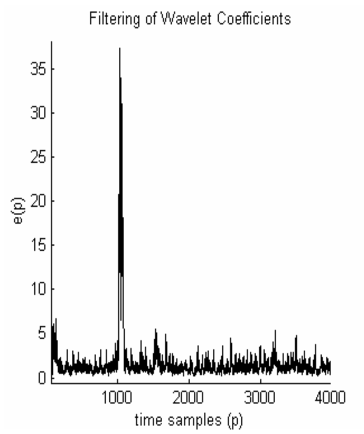


c)



d)

Fig 3: Wavelet analysis: X, Y and Z positional data has been acquired from an EM tracker attached on the skin of a healthy subject in order to assess the wavelet technique of filtering sudden movements similar to those that are introduced in a bronchoscopy session when the patient coughs. We used Daubechies (db10) mother wavelets to analyze the signals. a-b-c demonstrate the three positional (x,y,z) signals and the correspondent wavelet coefficients. e) Demonstrates the energy function after analyzing the X-motion signal. Similar results have been acquired from analyzing either the Y or the Z component.

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