Motion Complexity Analysis with Automated Lung Field Tracking in MRI Temporal Sequences
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Abstract: We propose a new method for evaluating the lung field motion complexity in magnetic resonance (MR) image temporal sequences, where complexity is defined as the minimum number of respiratory movement patterns to represent the detected lung field motion. In the first part of this work, a method for high precision landmark determination and tracking on a temporal sequences of chest magnetic resonance images is proposed. The landmark determination and tracking algorithms are based on a hierarchical template matching algorithm. A stable matching is made with some additional rules to avoid mistracking. In the second part of this work, the optimum respiratory movement patterns are determined by minimizing the mean square error applied to the determined paths. The proposed algorithm was tested with 29 subjects, including healthy subjects and COPD (Chronic Obstructive Pulmonary Disease) patients. The paths obtained by the landmark tracking algorithm represent the movement of some parenchyma internal structures. The paths automatically obtained were analyzed and compared to paths manually obtained by a medical specialist. It is concluded that the respiratory movement patterns necessary to represent the paths determined manually and automatically for the same subjects were compatible. The results also show that COPD patients have two main respiratory movement patterns. Copyright ©2011 IFAC.

Keywords: sequential MR images, breath movement, feature points, PCA

1. INTRODUCTION

Accurate modeling of the lung motion is an important topic in several clinical applications. For example, in lung cancer radiotherapy the lung motion is used for planning margins (van Herk, 2004), 4D radiotherapy (Keall et al., 2005) and intensity modulated radiation therapy optimization (Sarrut et al., 2007). Recently, several techniques using four dimensional CT imaging (sequence of three dimensional CT images indexed by breathing state) were proposed (Sarrut et al., 2007; Boldea et al., 2008). However, CT uses ionizing radiation, which is particularly unsuitable for repeated studies.

Recently, advances in MR technology make possible researches related to respiratory movement determination (Matsushita et al., 2004), diaphragmatic motion (Iwasawa et al., 1999; Suga et al., 2000; Iwasawa et al., 2000, 2002) and four dimensional visualization (Tsuzuki et al., 2009; Sato et al., 2011). These researches are related to thoracic wall motion analysis, and few researches have been focused on the movement of the lung parenchyma (Gee et al., 2003; Voorhees et al., 2005).

By supposing that the internal organs must have continuous movement, the active contour model (snakes) was used to determine boundaries in time (Takahata et al., 1992). Matsushita et al. (2004) and Asakura et al. (2005) used a standard respiratory movement pattern to synchronize the lung movement in MRI temporal sequences. However, it is known that the lung does not move totally synchronously and this characteristic is more strong in COPD patients (Iwasawa et al., 2000, 2002). Some clinical trials have shown that COPD patients have paradoxical movement of the diaphragm (Iwasawa et al., 2000). In this work, it
is proposed a method to evaluate the respiratory movement patterns in minimum number that can represent the automatically detected landmark paths internally to the lung parenchyma. The proposed algorithm is applied to healthy subjects and to patients with COPD. The lung is composed by several highly elastic structures: vasculature, airways and parenchyma. Pulmonary diseases affect these structures and modify their elasticity in many different ways. This work is a first tentative to associate pathologies of the lung to respiratory movement patterns.

This work is structured as follows. Section 2 explains the proposed algorithm to automatically determine and track landmarks. Section 3 explains the proposed algorithm to evaluate the respiratory movement patterns in minimum number that can represent the landmark paths. Section 5 presents some results and the conclusions are in section 6.

2. LANDMARK DETERMINATION AND TRACKING

The proposed system determines the movement of landmarks present in temporal sequence of MR images. It consists in two phases as illustrated in Fig. 1. In the first phase, the lung parenchyma is determined and anatomical landmarks are automatically detected. In the second phase, the landmarks are registered according to a two steps algorithm. The first step creates an initial registration scheme based on the pattern matching (Hill et al., 2001), and the second step uses some robust constraints to avoid mistracking.

2.1 Automatic Landmark Detection

In previous works related to lung motion determination, the landmarks have been manually selected (Sarrut et al., 2007; Metzen et al., 2009). After determining the interior of the lung, two different shape detection algorithms are simultaneously applied to determine landmark candidates: circular shape detection and edge based shape detection. The circular pattern represents the intersection of a lung structure with the MR image plane (see Fig. 2). Circular patterns are searched internally to the lung mask, and they can be found by using the multiple separability filters with various radii (Fukui and Yamaguchi, 1998). The edge based shape detection evaluates edge distribution and edge intensity over a window. When 2D shapes, such as the fork pattern (see Fig. 2), is present the edge intensity average is high and the edge direction has wide distribution. It is defined a function \( E_{\text{tot}}(i,j) \) that makes a weighted combination of edge direction standard deviation \( D_{\text{dir}}(i,j) \) and average edge intensity \( S_{\text{mag}}(i,j) \)

\[
E_{\text{tot}}(i,j) = w_{\text{mag}} \cdot S_{\text{mag}}(i,j) + w_{\text{dir}} \cdot D_{\text{dir}}(i,j)
\]

where \( w_{\text{mag}} \) and \( w_{\text{dir}} \) are weights. If the value of \( S_{\text{mag}}(i,j) \) is considerable then it is possible that a landmark is present. The distinction can be realized by the edge direction standard deviation, a lower standard deviation indicates a non 2D landmark and a higher standard deviation indicates a 2D landmark. The application of a discriminant analysis algorithm to \( E_{\text{tot}}(i,j) \) defines a threshold that can separate circular landmarks. When \( E_{\text{tot}}(i,j) \) has a value greater than the threshold, then there is a great probability that a 2D landmark is present.

The vicinity of each landmark candidate is processed by a template matching to determine the presence of a similar shape in the same frame. The landmark candidate is the template. The algorithm determines the degree of similarity in the landmark candidate vicinity and if a similar shape is found then this landmark candidate is removed. Otherwise, the landmark candidate is considered as a landmark. This processing is made to diminish possible mistrackings, ensuring the pursuit of landmarks that are unique in a vicinity region.

2.2 Landmark Tracking

The vascular system has robust landmarks as its position and extension might change but its structure remains (nearly) constant (Metzen et al., 2009). Considering that the temporal sequence of images was acquired through MR devices, there is a big limitation. The pulsatile movement of the fluids inside the vessels affects the polarization of the magnetic field. Consequently, the vessel systems are visible only in some instants (Tavares et al., 2009). In general, mistracking can occur in some few situations: when a landmark has a large motion between two successive time frames, when through plane motion happens and when pulsatile movement of fluids is present. To overcome mistracking, the algorithm detects the topological configuration of landmark candidates. The topological configuration must be maintained between successive frames.

The topological configurations is defined by a structure with the three nearest landmarks is created (see Fig. 2). When comparing two adjacent frames, it is assumed that the topological configuration of the structure does not change. If a landmark is internal (external) to the triangle defined by the nearest three landmarks then in the following frame the same topological situation should be kept. The following constraint is used to ensure continuity between frames.

Fig. 1. Flow of the proposed algorithm.
Fig. 2. Example of edges connecting a landmark to the three nearest landmarks. It is possible to visualize two types of landmarks: landmark 2 has a fork shape and landmark 4 has a circular shape.

\[ r_{th1} \leq \frac{d_{k,n}}{d_{k,n-1}} \leq r_{th2} \]  \hspace{1cm} (2)

where \( d_{k,n} \) (\( k = 1, 2, 3 \)) is the distance between current landmark and the nearest \( k \) landmarks in frame \( n \). \( r_{th1} \) and \( r_{th2} \) are thresholds representing the limits that the distance between landmarks can vary between two adjacent frames.

The tracking algorithm uses a template matching algorithm, in the search for patterns in the next frame that are similar to the landmarks present in the current frame. The tracking must also obey the maintenance of the topological structure and the continuity condition defined by eq. (2). The template matching algorithm is defined by

\[ R_{CC} = \frac{\sum_{i=0}^{h-1} \sum_{j=0}^{w-1} I_0(x+i, y+j)T_0(i,j)}{\sqrt{\sum_{i=0}^{h-1} \sum_{j=0}^{w-1} T_0^2(i,j)}} \]  \hspace{1cm} (3)

where \( I_0(x, y) = I(x, y) - \bar{I} \), \( T_0(i,j) = T(i,j) - \bar{T} \). \( I(x, y) \) is the image and \( T(i,j) \) is the template with size \((h, w)\). \( \bar{I} \) and \( \bar{T} \) are the pixel intensity average in the image window and in the template, respectively. The position with largest \( R_{CC} \) is selected as next landmark position.

### 3. MOTION COMPLEXITY ANALYSIS

The path of the tracked landmarks can be expressed as a linear combination of respiratory movement patterns. In this section, it is described an algorithm that determine a set of optimum respiratory movement patterns that can represent a set of bidimensional paths, and the set of respiratory movement patterns is minimum.

Each path \( f(t) \) corresponds to a temporal sequence of landmark points \((x_1, x_2, \ldots, x_1, \ldots, x_n)\), a landmark point is represented as vector pair with the origin centered at their average (see Fig. 3(a)). A path \( f(t) \) has \( n \) elements and a complete path is represented as a point with \( n \) coordinates in \( \mathbb{R}^n \). In this case, points representing scaled paths \( a \cdot f(t) \) are located in a straight line (see Fig. 3). Thus, if all determined paths are synchronous to a single respiratory movement pattern, their associated points are located in a straight line in \( \mathbb{R}^n \). On the other hand, a path \( b \cdot g(t) \neq f(t) \), \( \forall b \in \mathbb{R} \), is not in the same straight line defined by \( a \cdot f(t) \). Fig. 4 shows paths that are linear combinations of \( f(t) \) and \( g(t) \). These paths are in a plane in \( \mathbb{R}^n \). Therefore, it is proposed an algorithm to determine the minimum required respiratory movement patterns and their contribution ratio to represent all determined paths for a given subject.

Considering that \( a \) is the searched respiratory movement pattern, the determined paths are represented by \( x \) (points in \( \mathbb{R}^n \)), the mean square error method gives that

\[ S_e = \frac{1}{m} \sum_{i=1}^{m} \Delta x_i^2 \]  \hspace{1cm} (4)

\[ = \frac{1}{m} \sum_{i=1}^{m} [x_i^T a - (x_i^T a)^T (x_i^T a)] \]

\[ = \frac{1}{m} \sum_{i=1}^{m} x_i^T x_i - a^T \left[ \frac{1}{m} \sum_{i=1}^{m} x_i x_i^T \right] a \]

\[ = \frac{1}{m} \sum_{i=1}^{m} x_i^T x_i - a^T V a \]
where $V$ is the correlation matrix. Since, $\sum_{i=1}^{m} x_i^T x_i$ is constant, and in order to minimize $S$, it is necessary to maximize $a^T V a$. In order to avoid mistracking, it is assumed that the path generated by the landmark tracking is smooth and the movement between two frames is averagely small. Additionally, it is considered that $a$ is a unit vector. Defining matrix $D$ by

$$D = \begin{bmatrix} 2 & -1 & 0 & \cdots & -1 \\ -1 & 2 & -1 & \cdots & 0 \\ \vdots & \vdots & \ddots & \ddots & \vdots \\ -1 & 0 & \cdots & -1 & 2 \end{bmatrix} \quad (5)$$

Then, $Da$ is a second derivative vector. The smoothness of the respiratory movement pattern $a$ can be evaluated by $\|Da\|^2$. Then, it is necessary to maximize

$$S = a^T V a - \lambda (a^T a - 1) - \alpha \|Da\|^2 \quad (6)$$

where $\alpha > 0$. Considering that $W = V - \alpha D^T D$, expression (6) can be rewritten.

$$S = a^T W a - \lambda (a^T a - 1) \quad (7)$$

Note that we previously researched motion complexity analysis (Yanagita et al., 2009), but the errors from the tracking algorithm may affect the complexity analysis. In this paper the influence of tracking errors is reduced by minimizing the mean square error with a smoothness additional condition.

$S$ must be maximized, then

$$\frac{\partial S}{\partial a} = 2W a - 2\lambda a = 0 \quad (8)$$

Resulting $Wa = \lambda a$, this is very similar to the principal component analysis method directly applied to the paths. The covariance matrix $\frac{1}{m} \sum_{i=1}^{m} (x_i - \hat{x}) (x_i - \hat{x})^T$ is replaced by matrix $W$. This method determines the eigenvalues of $W$ (where, $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_n$) and eigenvectors $a_1, a_2, \cdots, a_n$ (principal component vectors). The determined eigenvectors represent the optimal respiratory movement patterns. The eigenvalues represent the variances associated to the corresponding eigenvectors that minimizes the value of $S$.

Considering that the landmark path is smooth and that using just the first $i$ respiratory movement patterns the landmark paths can be optimally represented according to the mean square errors method. Then

$$\Delta S = \frac{\sum_{j=i+1}^{n} \lambda_j}{\sum_{j=1}^{n} \lambda_j} \quad (9)$$

is the residual ratio of mean square error, and $1 - \Delta S$ represents the fitting accuracy ratio when using the first $i$ patterns, which corresponds to the contribution ratio in the principal components analysis.

4. MATERIALS AND METHODS

The sequences of MR images used in the experiment were obtained with subjects lying supine inside a 1.5 T Intera (Philips Medical Systems). A total of $48 \sim 80$ sagittal images from 29 subjects were obtained over the right lung at full inspiration and full expiration. 5 subjects are healthy and 24 are COPD patients. The classification of the COPD patients are 4 in stage I, 10 in stage II, 8 in stage III and 2 in stage IV. The sequence was a balanced FFE (TR = 2.2 msec; TE = 1.1 ms); one frame acquisition time = 0.28 s, field of view (FOV) = 450 mm, matrix size = $256 \times 256$ pixels and 12 bits per pixel. In this work, the size of the template is $9 \times 9$ pixels. The window to search for landmarks was defined as three times the size of the template, in this case as $27 \times 27$ pixels.
Table 1. Comparison of the determined respiratory motion patterns (MP) contribution rates obtained from manual tracking (Yanagita et al., 2009)

<table>
<thead>
<tr>
<th></th>
<th>1st MP</th>
<th>2nd MP</th>
<th>3rd MP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normal</td>
<td>93.5 ± 1.8%</td>
<td>3.3 ± 2.0%</td>
<td>0.5 ± 0.2%</td>
</tr>
<tr>
<td>Stage I</td>
<td>89.9 ± 3.9%</td>
<td>3.8 ± 2.7%</td>
<td>1.2 ± 0.4%</td>
</tr>
<tr>
<td>Stage II</td>
<td>87.1 ± 6.9%</td>
<td>6.7 ± 4.1%</td>
<td>0.9 ± 0.3%</td>
</tr>
<tr>
<td>Stage III</td>
<td>89.9 ± 4.0%</td>
<td>3.5 ± 1.6%</td>
<td>0.9 ± 0.5%</td>
</tr>
<tr>
<td>Stage IV</td>
<td>81.2 ± 2.6%</td>
<td>7.4 ± 3.7%</td>
<td>2.4 ± 1.6%</td>
</tr>
</tbody>
</table>

Table 2. Comparison of the determined respiratory motion patterns (MP) contribution rates obtained from automatic tracking

<table>
<thead>
<tr>
<th></th>
<th>1st MP</th>
<th>2nd MP</th>
<th>3rd MP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normal</td>
<td>94.7 ± 2.5%</td>
<td>4.5 ± 1.7%</td>
<td>0.7 ± 0.4%</td>
</tr>
<tr>
<td>Stage I</td>
<td>88.8 ± 5.0%</td>
<td>4.9 ± 2.2%</td>
<td>1.7 ± 0.9%</td>
</tr>
<tr>
<td>Stage II</td>
<td>86.2 ± 6.0%</td>
<td>6.5 ± 2.8%</td>
<td>2.1 ± 1.5%</td>
</tr>
<tr>
<td>Stage III</td>
<td>90.4 ± 4.3%</td>
<td>4.3 ± 1.9%</td>
<td>1.5 ± 0.9%</td>
</tr>
<tr>
<td>Stage IV</td>
<td>84.7 ± 4.0%</td>
<td>9.3 ± 7.0%</td>
<td>2.2 ± 1.6%</td>
</tr>
</tbody>
</table>

5. RESULTS

Figure 5 shows examples of automatic detected landmarks. Blood vessels that intersect the sagittal image plane with circular and fork patterns are detected. Fig. 6 shows examples of automatic landmark tracking. In this figure, the path has an approximately elliptical shape. Fig. 6 shows a zoom of some selected landmark paths. The detected paths show the hysteresis of the lung motion. The protocol was approved by the hospital medical-ethics committee of Kanagawa Cardiovascular and Respiratory Center, and informed consent was obtained from each patient.

Cao and Ruan (2007) pointed that the verification of medical image registration algorithms is still a problem, because the definition of the golden standard is very difficult. To verify the effectiveness of this technique, the same procedure was executed manually by a medical expert (Yanagita et al., 2009) and compared to the results obtained from the proposed algorithm. It is possible that the medical expert and the proposed algorithm select different landmarks. Instead of comparing the pixel coordinates of the manual and automatic determined paths, we compare the contribution rate for each respiratory movement pattern. The algorithm described in section 3 is applied to the paths obtained from both methods (manually and automatically) and the contribution ratio for each respiratory movement pattern is determined.

Tables 1 and 2 show the mean and standard deviation of the contribution ratio for each respiratory movement pattern classified by subject category. According to this result, COPD patients have lower accumulative contribution when compared with healthy subjects. On the other hand, the standard deviation associated with the COPD patients have higher. The manually obtained results and those obtained from the proposed algorithm are compatible. In healthy subjects, the first motion pattern contributed with more than 94%. On the other hand, COPD patients have a similar rate of 94% from the first and second motion patterns, suggesting that two motion patterns are present.

Fig. 8.(a)-(b) shows the comparison of the first-second respiratory movement patterns contribution ratio obtained manually and automatically, respectively. Each data point represents a different subject and its shape represents subject different categories. The contribution ratio from the respiratory movement patterns obtained manually and automatically are very compatible, because all points are almost within a 45° line. Fig. 8.(c) shows some incompatibility between the third respiratory movement pattern contribution ratio obtained manually and automatically. Considering that the third respiratory movement pattern contribution ratio is very low (approximately 1.5%, see Tables 1 and 2) and that the discrepancy between the automatically and manually third respiratory movement pattern contribution ratio is nearly 3.5%. The manual approach is executed by placing the mouse over landmarks, and such process suffers a precision of 2 ∼ 3 pixels. It is possible to conclude that such discrepancy can be resulted from the manual processing, where the pixel cannot be precisely selected.

6. CONCLUSIONS

In this paper, landmark detection, tracking and complexity analysis algorithms are proposed. The proposed algorithm was tested with MR temporal data sets from 29 subjects. A medical specialist manually executed the landmark determination and tracking. The paths obtained manually and automatically by the landmark tracking were analyzed and the respiratory movement patterns necessary to represent them were compatible. Our results have shown that, according to the available data sets, it is necessary to have at least two respiratory patterns to represent landmark movements from COPD patients.

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REFERENCES


