Adaptive Cross Filtering: A Method For Enhancement and Detection of SPAMM Grid Tags

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Introduction:

Two-dimensional SPAMM tagging is a technique that spatially modulates the magnetization of tissue at right angles to an MR imaging plane producing a grid of equally spaced dark lines (see Fig 1a). If applied to an initial image and followed over time the relative movement of the intersection points of the grid can be used to calculate the mechanical properties of the tissue. Manual analysis of tagged images is extremely laborious and subject to inter- and intra-observer differences. Even current semi-automated techniques such as active contour analysis require significant user interaction. Our aim is to develop an adaptive filtering process that extracts tag information in an easy, fast, consistent and accurate way.

Method:

Take the image as a two dimensional indexed set $M = m_{ij}$, $i,j \in \{1,2,\ldots,256\}$ (see Fig 1a). For A, $B \subset M$ and $m_{ij} \in A \cap B$, we define a *maximum cross filter*, $X_{max}(m_{ij}) = \max[\text{mean}(A),\text{mean}(B)]$ and a *minimum cross filter*, $X_{min}(m_{ij}) = \min[\text{mean}(A),\text{mean}(B)]$. Assume that the tags are low intensity (value) regions in M. The maximum cross filter results in a low intensity pixel only when both A and B are low intensity (i.e. are contained mostly in the tagged regions). These correspond to when m_{ij} is an intersection point. The minimum cross filter on the other hand will result in a low intensity pixel when either A or B is low intensity and, because it relies on the mean, results in low pass filtering. We evolve A and B over time so as to approximately conform to the tagged regions at each phase and position.

We choose a subset of the image, $M^* \subset M$, that contains the relevant tags. Here $i_{\alpha\beta} \in M$ are the intersection points with $\alpha \in \{0,1/\kappa,2/\kappa,\ldots,(\kappa-1)/\kappa,1\}$ and $\beta \in \{0,1/\lambda,2/\lambda,\ldots,(l-\lambda)/\lambda,1\}$ corresponding to the ordered $\kappa+1$ horizontal and $\lambda+1$ vertical tags respectively. At each phase the algorithm then proceeds as follows:

1. The original tagged image of the current phase is processed to reduce the contrast between different regions while maintaining tag structure. This is achieved by subtracting a Gaussian filtered M from M (see Fig 1b).
2. We construct the partition $\Lambda = K \times \Gamma$, $K = \{0,1/\kappa,2/\kappa,\ldots,(\kappa-1)/\kappa,1\}$ and $\Gamma = \{0,1/\lambda,2/\lambda,\ldots,(l-\lambda)/\lambda,1\}$. For the set of intersection points, I, we generate $T = \{t_{\alpha\beta}, = i_{\alpha\beta} : i_{\alpha\beta} \in I \subset M^*, (\alpha,\beta) \in \Lambda\}$ which equates to the co-ordinates of the tag intersection points within M* in the previous phase. In phase 1 $i_{\alpha\beta}$ is estimated from the known spacing and position of undeformed tags. A refined partition, Λ^+, is generated using a *partition quotient*, q, by replacing κ and λ with $\kappa^+ = q\kappa$ and $\lambda^+ = q\lambda$ respectively. Using 2-D cubic interpolation over Λ^+ we produce a denser set $T^+ = \{t^+_{\alpha+\beta+} : (\alpha^+,\beta^+) \in \Lambda^+\}$. We choose q so that $M^* \subset \text{image}(T^+)$. The required value of q can vary from 1-1.5 times the tag spacing, Δt, depending on the amount of tag distortion.
3. For each point $m_{i_0j_0} \in M^*$ the sets A and B are chosen centered on $t_{\alpha_0\beta_0} = (T^+)^{-1}(m_{i_0j_0})$ such that $A = \{t_{\alpha_0\delta} : t_{\alpha_0\delta} \in T^+, \delta \in [\beta_0 - qc_h, \beta_0 + qc_h]\}$ and $B = \{t_{\delta\beta_0} : t_{\alpha_0\delta} \in T^+, \delta \in [\alpha_0 - qc_w, \alpha_0 + qc_w]\}$, where qc_h and qc_w are the *cross-height* and *cross-width* scaled by the partition quotient, q, to account for the refined partition above. For a tag spacing of Δt, c_h and c_w are chosen to be $0.45 \times \Delta t$.
4. Next we apply the minimum cross filter to each point $m_{ij} \in M^*$ using the A and B defined in step 3. The result, $X_{min}(M^*)$, produces smoothing of the image while preserving tag structure (see Fig 1c). We have chosen A and B perpendicular in T^+. Assuming only slight distortion of the tags from one phase to the next, the filter will follow the approximate course of the tags within M*.
5. The maximum cross filter is applied to the minimum cross filtered image to yield $X_{max}(X_{min}(M^*))$ (see Fig 1d). This results in localized regions of low intensity corresponding to the tag intersection points (see Fig 1d).
6. To find the co-ordinates of the intersection points we generate an *intersection point map* by adding $\nabla_x(\nabla_x(X_{max}(X_{min}(M^*))))$ and $\nabla_y(\nabla_y(X_{max}(X_{min}(M^*))))$, the double gradients of the maximum cross filtered image in the horizontal and vertical direction respectively. The local positive maxima in the neighborhood of each previous tag intersection point, $i_{\alpha\beta} \in I$, will correspond to the new intersection point (see Fig 1e).
7. Repeat steps 1-7 until all phases are exhausted.

Results:

The algorithm was implemented in MATLAB® and applied to an ultra-fast MR grid tagging sequence of lungs[1]. Figure 1 demonstrates the process applied to the second phase of the data. Figure 2 shows the tracked points superimposed on the left lung over the first 4 phases.

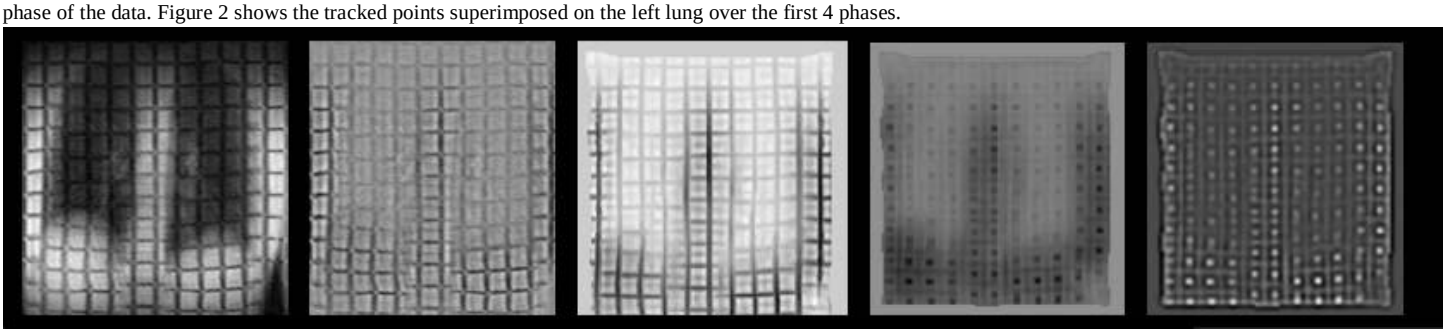

Figure 1: Second phase of a dynamic lung tagging series: a. Raw image; b. Subtracted image; c. Minimum cross filtered image; d. Maximum cross filtered image; e. Double gradient image.

Discussion:

The algorithm is quite robust and works accurately for most intersection points in the series. Strengths lie in speed and consistency. The algorithm does however depend on accurate tracking from phase to phase and so an error in a preceding phase may propagate. With the addition of regularizing methods for point spacing and human supervision/guidance between phases the technique should provide a promising semi-automated method of tag tracking which is easily amenable to any tissue (e.g. cardiac, MSK). Problems do arise where shear results in tag discontinuity between different tissue, for example between the lung and adjacent chest wall. If this occurs along a tag line a set of two intersection points may result, although any such points are probably not important in the determination of mechanical properties. As with all techniques designed for tag tracking, tag fading may limit the process in later phases.

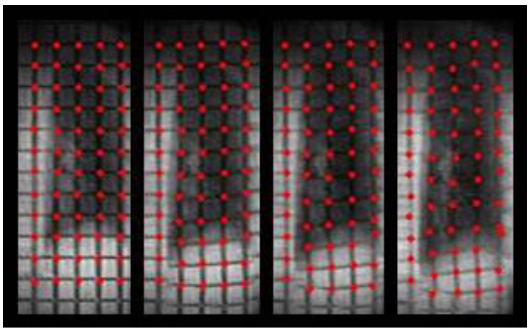

Figure 2: Adaptive cross-filtering algorithm applied to the left lung over first 4 phases in a dynamic lung tagging series.

References:

1. Chen Q, Mai VM, Bankier AA, et al. An ultra-fast MR grid tagging sequence for assessment of local mechanical properties of the lungs. Magn Reson Med 2001;45:24-28.