Tissue stiffness estimation using gaussian filters for prostate MR elastography

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Introduction

Manual palpation through digital rectal examination is an established method for prostate cancer screening. Unfortunately, the technique is highly subjective and has limited spatial resolution. Prostate MR Elastography (MRE) could address these shortcomings by mapping stiffness throughout the entire gland. Recent work suggests that intracavitary approaches using transurethral actuators can generate the frequency and amplitude of shear wave motion in the prostate gland necessary to detect clinically relevant tumours [1]. The Local Frequency Estimation (LFE) algorithm [2] [3] [4] has been used successfully in a number of applications to calculate shear stiffness from shear wave images acquired with MRE. In comparison with other tissue property reconstruction methods, it produces minimal amounts of image artifacts and does not require smoothing [5]. By modifying conventional LFE algorithms from the literature, elastogram resolution was increased without increasing noise, and controls are introduced where the user can, at runtime, fine-tune the tradeoff between high resolution and low noise, as the situation demands.

Methods

The LFE algorithm first filters the wave images with pairs of frequency-dependent filters in Fourier space. The dominant local frequency is a function of the signal amplitude ratio at each point in the spatial domain. The conventional implementation of LFE uses lognormal filters. In our approach, a set of filters in Fourier space are described by Gaussians centered at selected frequencies ρ_j:

$$f_j(x) = \exp\left(\frac{-(\rho_j - x)^2}{2\sigma^2}\right) \quad (1)$$

where f_j is the j-th filter in the set, x is the frequency, σ is the width of the filter, and ρ_j is the center frequency for the j-th filter. Gaussians are chosen because they are optimally compact in both frequency and spatial domains, minimizing image artifacts at any given resolution. Filters are centered at different frequencies so that the filter width, an important determinant of LFE performance, is kept constant between filters. Furthermore, the filter width can be adjusted at runtime, to the requirements of the clinician, to achieve the desired tradeoff between elastogram resolution and noise. The LFE technique is extended to 2D images in much the same way as described by Knutsson *et al.* [2].

LFE works only when enough signal is left after filtering, so to estimate frequencies over a wider bandwidth, a weighted average of estimated frequency from each pair of adjacent filters is taken. To suppress noise, the weights are modified, from the conventional approach, to the product of the signal strengths after filtering by each of the two filters. To further eliminate artifact, an iterative method is implemented to narrow the total bandwidth of the filters, effectively reducing the influence of noise in the reconstructed elastograms. After each iteration, the area occupied by each frequency is calculated, and those frequencies (upper and lower) occupying less than 0.1% of the total area of the elastogram are eliminated in the next iteration. This was repeated until the change in cutoff frequencies between iterations was less than $10m^{-1}$, or about 2% of frequencies in Fourier space for a typical wave image, indicating that most of the frequencies containing only noise had already been cut off.

Evaluation and Results

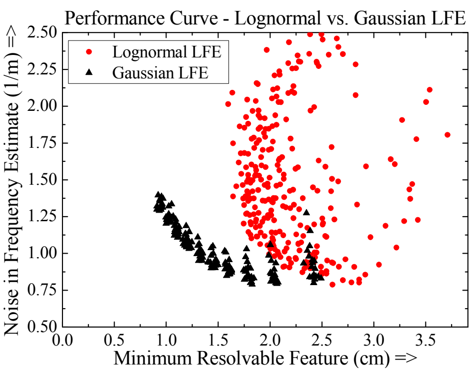

Fig. 1: Noise vs. resolution for lognormal and Gaussian LFE. Each point represents an LFE under a unique set of parameters.

The performance of this modified algorithm was first compared with the conventional LFE algorithm employing lognormal filters on a 1D sinusoidal signal with a sharp transition in spatial frequency from $150m^{-1}$ to $100m^{-1}$ and 10% Gaussian distributed noise. The distance required to estimate the spatial frequency around the transition point to within $5m^{-1}$ of the correct value measured as the LFE resolution, and the standard deviation of the frequency estimate outside the transition region was measured and used to characterize noise. Figure 1 demonstrates that the Gaussian LFE is more stable and is able to transition between spatial frequencies more quickly than the conventional LFE.

The performance of this modified algorithm on MRE data was investigated by computing the elastogram from shear wave images obtained using a transurethral actuator in a 1.5% agar phantom with 4 stiffer embedded inclusions at 2% and 2.5%, with diameters of 9.6mm and 6.4mm. The shear wave frequency in these experiments was 800 Hz, and wave images were acquired on a 1.5T MRI using a standard quadrature head coil. Figure 2 shows the wave image, elastograms calculated using MRE/Wave (Mayo Clinic, [3]), which employs the standard LFE algorithm, and those calculated with the proposed Gaussian LFE. Note the Gaussian LFE (Fig. 2D) showed sharper transitions between background and inclusion stiffness, and is the only elastogram to accurately estimate the stiffness of the smaller bottom inclusion (2.5% agar, 49 kPa [6]). At the same time, the stiffness estimate of the background gel in Fig. 2D is less noisy than that of 2C, and contained less ring-like artifacts. However, artifacts remain a problem where the signal-to-noise ratio in the wave image was poor.

Conclusion

A modified Local Frequency Estimation algorithm using moving Gaussian filters has been developed for MRE. The modified LFE algorithm features a variable, user-selected filter width, allowing the user to modify the LFE performance characteristics at runtime, trading resolution for lower noise, or vice versa, as well as a built-in mechanism to automatically select the frequency band that the LFE is sensitive to. Furthermore, the algorithm shows improved resolution and noise characteristics over conventional LFE algorithms using lognormal filters.

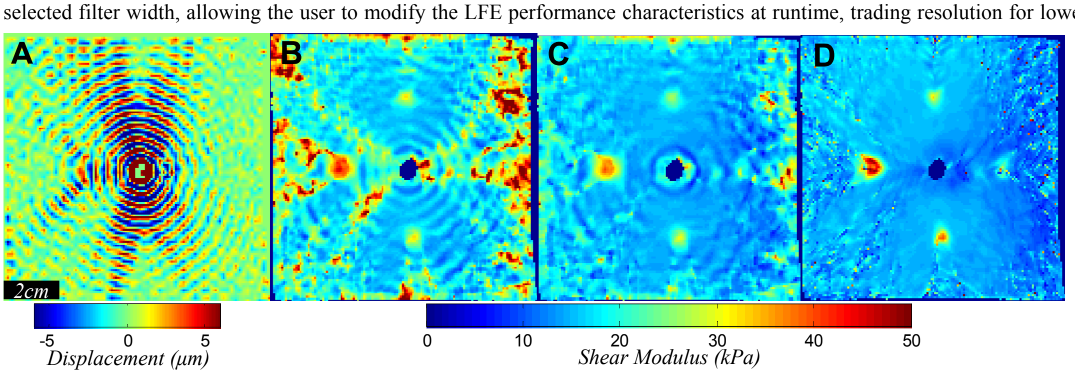

Fig. 2: Elastogram of agar gel phantom with stiff inclusions. A: Raw MRE wave image. B: Elastogram computed by MRE/Wave [3], no bandpass filtering. C: MRE/Wave elastogram after bandpass filtering, using the same frequency band as D. D: Elastogram computed from Gaussian LFE, using automatic bandwidth selection and filter width $\sigma = 70m^{-1}$

References

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