Proper Orthogonal Decomposition for Improved Assessment of Brain MR Elastography: Initial Results

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Introduction

Magnetic Resonance Elastography (MRE) is a promising methodology used to noninvasively image externally driven shear waves in soft biological tissues, in order to determine the local shear stiffness of the excited tissue [1]. Recent MRE studies of the brain have focused on how the mechanical properties of gray and white matter change in various disease states [2, 3, 4]. Standard MRE post-processing techniques use the known driving frequencies and the measured wavelengths to determine local stiffness, which requires the extraction of corresponding harmonic modes using Fourier decomposition [5]. Fourier mode decomposition is adequate if we assume that the mechanically actuated brain behaves like a linear dynamic system. However, recent studies have revealed a wide spectrum of responses [3] as the actuation parameters vary and this, coupled with the fact that the brain is a complex and ostensibly nonlinear mechanical system, motivates us to seek a more appropriate decomposition method of the MRE signal. We propose here the use of Proper Orthogonal Decomposition (POD) to extract the shear wave modes generated and measured within the brain by MRE. POD has previously been used in medical imaging to estimate the physiologic motion of the liver prior to ultrasound elastography [6]. We apply here POD to characterize the motion generated in a brain slice, and then compare it to Fourier mode decomposition for three actuation intensities. This is the initial step towards creating a low-dimensional dynamic model of the imaged part of the human brain, with the dual aim to reduce the acquisition times and improving the analysis of MRE data.

Methodology

Theory: POD approximates optimally a temporally varying field using a set of time-invariant basis functions (modes) multiplied by time-dependent weighting coefficients [7]. A time series of N 2-D phase contrast images can be converted to displacement and represented as $\xi(x_i,y_j,t_n)$. Using the "snapshot " POD method,, the images can be decomposed as follows:

$$\xi(x_i, y_j, t_n) = \sum_{k}^{K} \phi_k(x_i, y_j)\, a_k(t_n)$$

POD returns K modes which are the eigenfunctions of the space-correlation tensor, and constitutes a nonparametric method of decomposition which is not affected by nonlinearities or closely-spaced modes [7]. In this sense, POD is a more accurate method of decomposition than the Fourier transform, which may obscure or misrepresent modes due to the frequency resolution limits inherent in the method. Due to its ability to handle nonlinearities in the system, the time-invariant basis functions returned by the POD algorithm will also remain constant regardless of changes in certain parameters, such as intensity of mechanical actuation. For a nonlinear system, it is very difficult to estimate the response due to a change in a parameter, and using a Fourier decomposition method would require repeating experiments across all values of the modified parameter in order to create a complete dynamical model. The basic premise of the decomposition method is that the POD modes do not vary as the parameter changes, thus allowing for an accurate assessment of mechanical properties across multiple experiments, and the creation of an economic dynamic model of the brain with fewer scans.

In Vivo Experiment: In order to test the validity of the basic premise, we need to examine how the models returned by both POD and Fourier decomposition vary with changes in mechanical actuation intensity. Brain MRE data sets were acquired on a human volunteer with three different intensities, labeled 1x, 2x, and 4x. Actuation intensity refers to the amplitude of the harmonic actuation as controlled by the voltage input to the amplifier and shaker which drive a rocker apparatus via a long rod that shakes the head in a "nodding" motion at 50 Hz. Acquisitions sensitized to through-plane displacement were made with a single-shot spin-echo EPI sequence on a Siemens 3T Allegra scanner. Forty equally-spaced phase offsets were acquired over one period of actuation for high temporal resolution. Prior to decomposition by POD or Fourier, the appropriate image subtraction was performed, displacement was calculated from phase, and bulk motion and noise were removed with a spatial Butterworth bandpass filter.

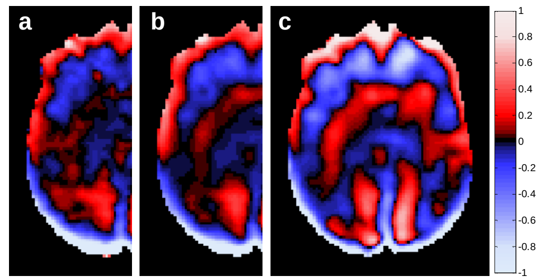

Fig. 1: Most energy enriched mode calculated by POD for three different intensities of mechanical actuation, **a)** 1x, **b)** 2x, and **c)** 4x. Data has been normalized relative to the 4x intensity data set.

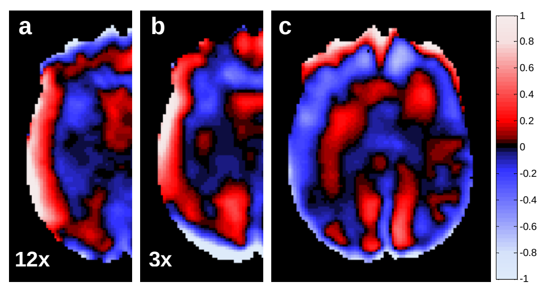

Fig. 2: Most energy enriched mode calculated by Fourier transform for three different intensities of mechanical actuation, **a)** 1x, **b)** 2x, and **c)** 4x. Data has been normalized relative to the 4x intensity data set. Contrast had to be increased by the factor in bottom left for the other sets for comparison.

Results & Discussion

The three data sets, corresponding to three different levels of actuation, were separately decomposed using both POD and the Fourier transform. The basis functions returned by the two techniques, ordered by their energy content, were compared across the three levels of external actuation intensity (thereafter referred to as the "parameter") in order to gauge how they vary with the change in parameter value. Specifically, the most energy-enriched mode was analyzed, as it is the dominant mode and it is typically used for further calculations and modeling. The basis functions returned by the POD algorithm for the three different intensities of mechanical actuation are shown in Figure 1. It can be seen that the basis functions are very similar for all three intensities. It should be noted that for the experiment with the lowest intensity actuation, there is a low contrast-to-noise ratio, resulting in a "blurring" between the nodal lines. The basis functions returned by Fourier analysis are shown in Figure 2, and it is evident that for the different actuation intensities, the first Fourier mode changes significantly, especially between 2x and 4x. These results indicate that the actuated brain can behave in a nonlinear fashion even under harmonic actuation. If the system was indeed linear, the Fourier bases would not only remain constant in shape with varying parameter, but would also scale in intensity in proportion to the parameter. The Fourier modes shown in Figure 2 had to be scaled judiciously to achieve similar contrast for comparison of mode shape; however they did not scale linearly with the parameter. In contrast, the results of Figure 1 were extracted by scaling with the appropriate factors (1, 2 and 4, approximately). This implies that extracting POD modes does not require but a single experiment with one actuation intensity.

Conclusions

Our initial results indicate that the most energetic mode returned by POD decompositions remains spatially invariant across the different values of the actuation parameter, and that the MRE signal corresponding to this mode scales proportionally with that parameter. By relaxing the assumption that the brain behaves like linear system in an MRE experiment, POD mode extraction, followed by system dimension reduction [7], can be used to ultimately develop a simple dynamic model of the imaged section of the human brain. Employing POD instead of Fourier decomposition with standard MRE inversion techniques promises to shorten acquisition times and reduce the variance in measured tissue stiffness between experiments, and even across studies.

References

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