Frame-to-frame statistics of Real-time strain images

A. Pesavento[1], A. Lorenz[1], H. Ermert[2], H. Sommerfeld[3], M. Garcia-Schürmann[3], Th. Senge[3], S. Philippou[4]
[1]Lorenz & Pesavento IT, Bochum, Germany, lp@lp-it.de
[2]Dept. of Electrical Engineering, Ruhr-University Bochum, Germany
[3]Dep. of Urology, Ruhr-University Bochum, Germany
[4]Dep. of Pathology, Ruhr-University Bochum, Germany

Abstract - This paper assesses the second order statistical properties of strain images with respect to the temporal direction. Successively acquired strain images in a real-time or similar off-line strain imaging system are correlated. This can be described by a covariance function, which is investigated in this paper by simulations. We will determine how the statistic properties will affect the choice of the frame-rate in a real-time strain imaging system and furthermore the effect of temporal filtering of strain images is discussed.

INTRODUCTION

Recently, we introduced the first real-time strain imaging system world wide [1], which uses a conventional desktop PC. The system uses phase-root seeking algorithm for strain estimation decribed in [2].

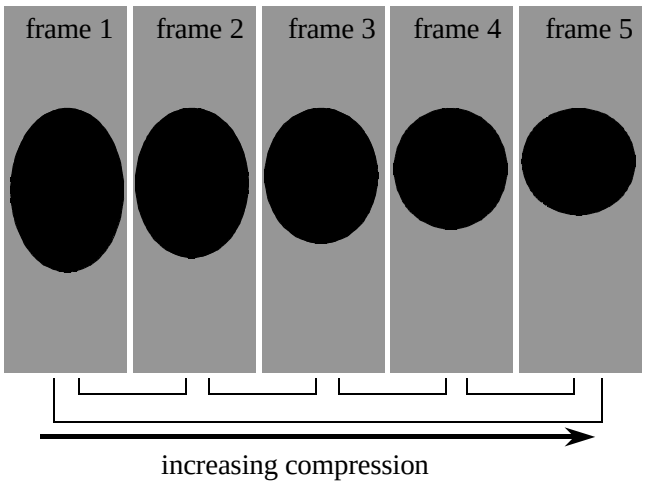

Figure 1: Strain images can be estimated by comparing frame 1 and frame 5 or by summing up the four strain images obtained by comparing successive frames.

It displays strain images with frame rates up to 30 frames per second. The calculation of one image pixel currently takes 3.5 µs . For instance images with 148 x 96 pixel can be calculated with 20 frames per second. These are the settings we use for prostate imaging. We have already shown in [3], that although phase root seeking is fast, it is a very accurate algorithm and the strain estimation reaches the corresponding Cramer Rao Lower Bound.

In conventional off-line strain imaging, two or more rf-frames are acquired from tissue under nearly constantly increasing or decreasing compression. Real-time strain imaging works similarly, but the speed of the compression also plays an important role. The frame-rate of data acquisition together with the speed of tissue compression form the amount of compression between two rf-frames. Low compressions, either due to high frame rates of the data-acquisition or due to a slow compression speed, result in low SNR strain images. However, multiple successive frames of strain images can also temporarily be filtered for an [3] improvement in SNR. This is the analogon to the positive effects of multicompression approaches [4, 5, 6] in conventional off-line elastography.

The question we focus on in this paper is the following: is it better to use high-frame rate data acquisition, resulting in many low SNR strain images per second, which can be used for further filtering, or is it better to use lower frame rates, resulting in less but higher SNR strain images per

second and perform no or less temporal filtering of strain images. Fig. 1 illustrates this question: using a given amount of strain (given either by physiological reasons or being an amount of compression, that can reasonably be applied in a fixed time), the question has to be answered whether it is better to acquire several e.g. 5 rf-frames during this compression and form the resulting strain images using a summation of these strain images (4 in this example) or is it better to calculate one strain image using only the first comparing to the last rf-frame?

To answer this question, we have to look separately into the two different kinds of noise observed on strain images. First considering only decorrelation noise, which results from undesired tissue motion or speckle decorrelation, the answer is obvious: since the amount of this noise is proportional to the amount of applied strain (for higher strains the dependency is even of a higher order), it is favorable to divide the compression in as many high correlated frames as possible.

Another component of noise in strain images result from the noise of the rf-echoes. When looking at the Cramer-Rao-Lower Bound for strain estimation [7]

$$\sigma_s^2 \geqslant \frac{24\pi}{T_G^3}\left\{\int_0^\infty \frac{2\omega^2 C_{UU}^2(\omega)/C_{nn}^2(\omega)}{1+2C_{UU}(\omega)/C_{nn}(\omega)}\mathrm{d}\omega\right\}^{-1} \quad (1)$$

we see, that this noise is totally independent from the applied strain. In this expression $C_{UU}(\omega)$ denotes the power spectrum of the echo signals , $C_{NN}(\omega)$ denotes the noise spectrum and T_G the observation time. In this case, the answer seems obvious at first sight: a summation of several images with the same noise most often results in a sum with higher noise compared to the single images. However, to fully answer this question we have to take a look at the correlation of the strain in these single images.

FRAME-TO-FRAME CORRELATION

Consequently, we estimated the covariance function that describes the correlation of successively acquired strain images using simulations. This covariance function is denoted with $c(k)$, where k is the difference of the frame numbers of the two strain images. This covariance function describes the amount of correlation of one specific pixel of a strain image to the same pixel in a different strain image of the same compression sequence on the “slow” time axis.

To estimate $c(k)$ we simulated 30 A-lines with 2048 samples of echo signals of tissue under five increasing compressions. The simulated echo signals have fully developed speckle resulting from a large number of scatterers. The simulation is described in detail in [2]. The sampling rate was 30 MHz. The echo signals have Gaussian power spectra with a center frequency of 7.5 MHz and a relative bandwidth of 66 %. Noise with a rectangular spectrum within the transducer's bandwidth was added to the signals leading to SNRs ranging from 10 to 30 dB. The differential strain between two images was chosen very small 0.05 % (hence the total compression was 0.2 %). Note, that compressions for this simulation have to be very small, since we want to exclude decorrelation noise. The window length for the time delay estimation was 16 samples. All strain images have been estimated using phase-root seeking [2, 3].

Using the echo data, we first compared strain images obtained using the first and the last rf-frame of the compression sequence to those obtained by summing up all four strain images. The result was, that these two strain images not only have the same amount of noise, but are highly correlated, too. The correlation coefficient was 0.97.

Furthermore, the covariance function was directly estimated with the following result:

$$c(k) \approx \begin{cases} \sigma_s^2 & \text{for } k=0 \\ -0.5\,\sigma_s^2 & \text{for } |k|=1 \\ 0 & \text{for } |k|>1 \end{cases} \quad (2)$$

where σ_s^2 denotes the variance of strain estimations given by the CRLB in Eq. 1 as denoted above.

Note, that for $\Delta k > 1$, the strain images are uncorrelated, since the noise of the underlying rf-frames are uncorrelated.

Discussion of Simulation Results

Both results are consistent, since the variance $\sigma_{\bar{s}}^2$ of noise of a sum

$$\bar{s} = \sum_{i=1...k} s_i \tag{3}$$

of k successively acquired strain images s_k can be obtained using

$$\sigma_{\bar{s}}^2 = \sum_{i=1..k} \sum_{j=1..k} c(i-j) = \sigma_s^2 \tag{4}$$

Note, that for a sum over *uncorrelated* images, the resulting variance of the noise is $k\sigma_s^2$.

Consequently, when looking at noise resulting from imperfect rf-data (electronic and acoustic noise etc.) one may use any number of steps during the tissue compression and combine the resulting strain images to one strain image. The strain image may as well be estimated using a single big compression step, this will result in the same SNR. However, when looking at decorrelation noise, which is a major problem especially in in vivo situations, we decrease this kind of noise by increasing the correlation of the rf-frames due to an increase of the number of acquired rf-frames which decreases the compression between two frames.

In a real time strain imaging system the summation of successive rf-frames can be described by temporal filtering of strain images using a filter with rectangular impulse response (note that temporal filtering means a filtering of successive frames on the "slow" time axis and **not** axial filtering of one image). Such a filter is not ideal in this situation, because the user of the system experiences a time-lag between the application of a tissue compression an the visual reaction of the system, which is an increasing strain on the screen. This effect is less severe, if a recursive filter of the form

$$\bar{s}_m = s_m + p\, s_{m-1} \tag{5}$$

is used, where s_m denotes the m-th strain image. The filtering effect and the noise reduction of this filter is similar to the filter with the rectangular impulse response. Temporal filtering of strain images is described in detail in [1].

In vivo example

Fig. 2 shows an example images of a prostate in vivo acquired in real-time with 20 frames per

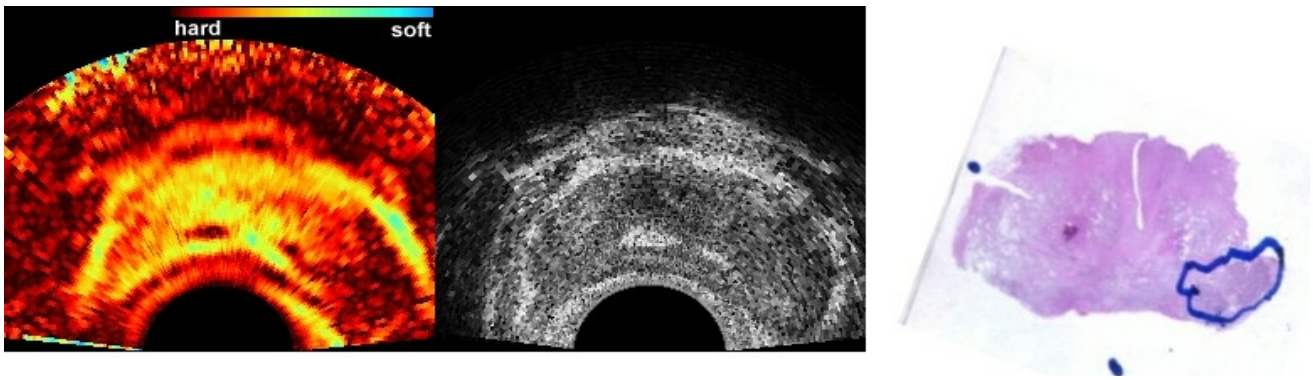

Figure 2: Comparison of an in vivo realtime strain image (left), B-Mode image (middle), and histology (right) of a prostate with tumor (marked by the contour in the histology)

second. The ultrasonic examination was performed prior to the radical prostectomy. The image shows a comparison of a real-time strain image, b-mode images and the histology of a prostate with carcinoma. The amount of compression between two of the acquired rf-frames is very low (<0.1 %). The filtering of several strain images leads to a high quality strain image.

Conclusion

In this paper, the frame-to frame statistic of real-time strain image was discussed. It was shown, that in a real-time strain imaging system, the frame rate can be chosen as high as possible, since a decrease in SNR due to the decrease in compression can fully be compensated by temporal filtering. On the other hand, high frame-rate real time strain imaging reduces decorrelation noise, which is especially important for in vivo imaging. Using a real-time strain imaging system with 20 frames/second the first in vivo real-time strain images of the prostate have been presented in this paper.

Acknowledgments

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