QUALITY CONTROL IN OFF-PUMP CORONARY ARTERY BYPASS SURGERY USING ULTRASOUND COLOR FLOW IMAGING WITH ADAPTIVE CLUTTER REJECTION FILTERS

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Abstract – Quality control in off-pump coronary artery bypass grafting (CABG) surgery can be done efficiently using ultrasound color flow imaging. Due to the excessive tissue movement of the beating heart, new methods for clutter filtering should be applied to properly separate the signal originating from blood, from the clutter artefact signals. Ultrasound data obtained from an experimental pig model undergoing CABG surgery was used to compare the commonly used polynomial regression filter to three adaptive filtering techniques for clutter removal. Results showed that the three adaptive filters outperformed the non-adaptive PR filter with better attenuation of clutter signal in the presence of uniform or accelerated tissue movement.

I. INTRODUCTION

Off-pump coronary artery bypass grafting (CABG) surgery is bypass surgery performed while the heart is beating. This technique of minimally-invasive surgery differs from conventional bypass surgery in which the heart is temporarily stopped and the patient is supported with a heart-lung machine. The potential advantages of doing off-pump CABG in selected patients include less postoperative morbidity and mortality, shorter recovery time for the patient, as well as less cost [1]. Intraoperative quality control has proven to be important in CABG surgery [2], and ultrasound color flow imaging (CFI) techniques, displaying images of tissue anatomy and blood flow, has proven to be highly valuable in this respect [2]. However, the excessive movement of the beating heart causes problems for the clutter rejection filters used in conventional ultrasound CFI methods. The clutter filters are unable to properly attenuate the signal from fast-moving tissue, resulting in flashing artefacts, i.e. coloring of areas in the image without blood flow. These artefacts conceal the actual blood flow, and in general disturb the surgeon. To reduce the amount of flashing artefacts, without removing signals from slowly moving adaptive clutter filters are needed. In this study, adaptation to the tissue movement is attempted with the intention of improving the attenuation of signal from tissue, leading to a better detection of the desired signal from blood. The method is based on a previous work on adaptive filters for clutter rejection by Bjærum et al [3].

The paper is organized in the following way. Section II includes experimental setup, data material and description of the filtering methods used in this study. In section III, the results of using adaptive and non-adaptive filters are compared and discussed. Finally, in section IV the principal conclusions of the study are drawn.

II. METHOD

Ultrasound data obtained from an experimental pig model undergoing CABG surgery was used in the study. The data was acquired with a GE Vingmed Vivid 7 ultrasound scanner with the GE i13L epicardial probe setup (linear phased array) as shown in Figure 1.

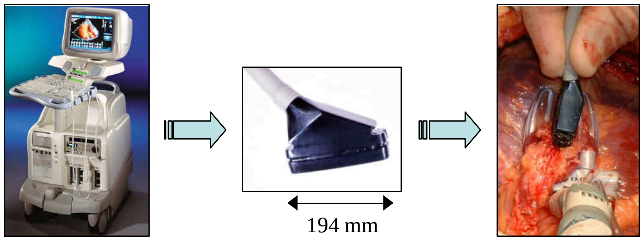


Figure 1: The GE Vingmed Vivid 7 ultrasound scanner, the GE i13L epicardial probe, and a field image of CFI quality control in CABG surgery

Relevant acquisition parameters are shown in Table 1. High frequency and high beam density made it possible to achieve CFI images with high quality. Effort was put into maximizing the spatial resolution in the color flow image, as the dimensions at hand are on a scale of millimetres.

CFI Parameter	*Value*
Center frequency	10 MHz
PRF	2,5 kHz
Packetsize	10
Radial resolution	0.16 mm
Lateral resolution	0.25 mm (Rayleigh)
Beam overlap	90%

Table 1: Relevant acquisition parameters

Typical images from the bypass graft are shown in Figure 2. The flashing artefacts are clearly visible in the bottom area of the images.

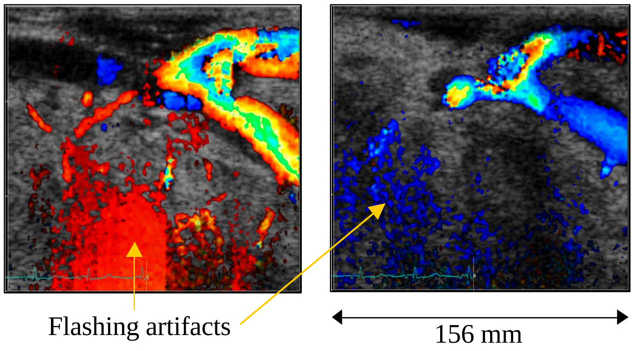


Figure 2: Flashing artifacts due to the clutter rejection filter's inability to suppress the signal from moving tissue. Systolic phase (left panel), diastolic phase (right panel)

Three different adaptive filters were compared to the non-adaptive polynomial regression (PR) filter [4] for clutter rejection:

1. The Mean Frequency (MF) Filter
2. The Varying Frequency (VF) Filter
3. The Eigenvector Regression (ER) Filter

Mean and varying frequency filters

The mean and varying frequency filters share the same basic setup shown in Figure 3.

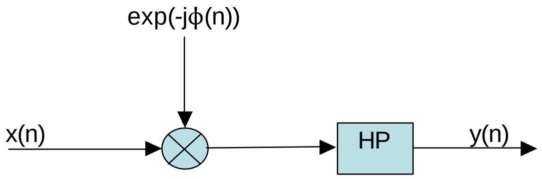


Figure 3: Block diagram of the mean and varying frequency filter operation

The complex demodulated RF signal from pulse to pulse is down-mixed with the estimated clutter Doppler frequency, followed by a high pass filter. In the study, a regular polynomial regression filter was used. For both filters the clutter movement is estimated from the phase of the auto-correlation function with lag one, averaged in space to ensure adaptation to tissue movement. The averaged auto-correlation estimate with lag one is given by:

$$\hat{R}_x(n,1) = \frac{1}{S}\sum_S x^*(n)x(n+1) \qquad (1)$$

where n is the pulse number within a packet of data, and S is the spatial averaging area. The difference in the two filters lies in the down-mixing phase term function $\phi(n)$, given by the following equation for the MF filter:

$$f(n) = v_c n = n\arg\left[\frac{1}{N-1}\sum_{n=0}^{N-2} R(n,1)\right] \qquad (2)$$

While the equation for the VF filter is given by:

$$f(n) = \sum_{k=1}^{n} \arg R(k,1), f(0) = 0 \qquad (3)$$

The MF filter down-mixes the signal with the mean phase term from pulse to pulse, corresponding to the mean velocity in the tissue area. The VF filter down-mixes the signal with the incremental phase term from pulse to pulse, which enables the VF filter to adapt to accelerated tissue movement [3].

Eigenvector regression filter

The ER filter's adaptation is based on the Doppler signal statistics. A correlation matrix is estimated by averaging in a spatial area where the tissue motion is more or less uniform. The correlation matrix estimate is given by:

$$\hat{R}_x = \frac{1}{K}\sum_{k=1}^{K} x_k x_k^{*T} \qquad (4)$$

where x_k is a vector of pulse to pulse time samples for one packet of data. The signal space of the correlation matrix is then spanned by its eigenvectors. Assuming the clutter signal is much stronger than the signal from blood and thermal noise, the largest eigenvalues will be dominated by the tissue clutter signal. Typically, the number K of eigenvalues from the clutter signal which exceeds the thermal noise level is limited, (in figure 4 K=3). The signal from blood, which has a different motion pattern, will have its energy in any part of the eigenvalue spectrum.

By removing the signal corresponding to the highest eienvalues, most of the clutter signal is removed, while a minimum amount of the signal from blood is lost.

The benefit of using the eigenvector basis, compared to e.g. the Legendre polynomial basis, is that the clutter signal spectrum will have minimum dimension; thus removing a minimum of enery from the blood signal [3].

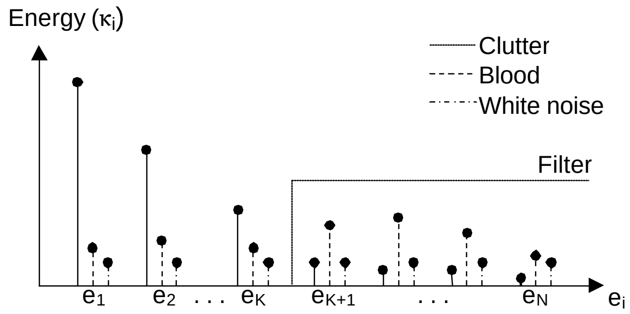


Figure 4: Clutter representation and filtering using the *K* eigenvectors of the signal correlation matrix with high energy

The clutter signal is represented by the following equation:

$$\hat{c} = \sum_{i=1}^{K} k_i e_i \tag{5}$$

where κ_i is the eigenvalue of the corresponding eigenvector. This is the discrete Karhunen-Loève expansion of the clutter space [5]. The clutter filtering can be expressed by:

$$y = \left(I - \sum_{k=1}^{K} e_k e_k^{*T} \right) x \tag{6}$$

where the signalvector *x* is projected into the complement of the clutterspace, producing the filtered output *y*.

For all three filters the correlation function or matrix was averaged in space on a range-beam grid. The number of lateral averaging areas was set equal to the number of interleave groups in the data to ensure proper correlation estimates.

III. RESULTS

The clutter filter performance was quantified by comparing the signal power before and after filtering, from a defined region inside and outside a vessel. The procedure was repeated for increasing filter basis size. A representative example is shown in Figure 5, which shows the complex demodulated (IQ) signal from inside and outside a vessel. Notice the accelerated tissue movement indicated by the IQ signal from the clutter region by the varying phase increments from sample to sample. Figure 6 shows the filter performance results using data from these regions. The figure shows that all three adaptive filters outperform the non-adaptive PR filter. It also shows that for a filter basis size of one to three the varying frequency and eigenvector regression filter has similar and superior performance.

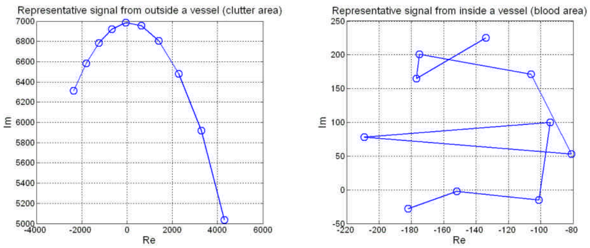


Figure 5: The complex demodulated signal from a representative region outside (clutter) and inside (blood) a vessel (to the left and right respectively)

For larger filter basis the varying frequency prevails. As the filter basis size was increased, the EV filter performance dropped to below that of all others in the study. A reason for this may be that the basis vectors spanning the blood subspace is then included and removed in the filtering process. This phenomenon can be observed in Figure 6 when the filters reach a basis size of five or more.

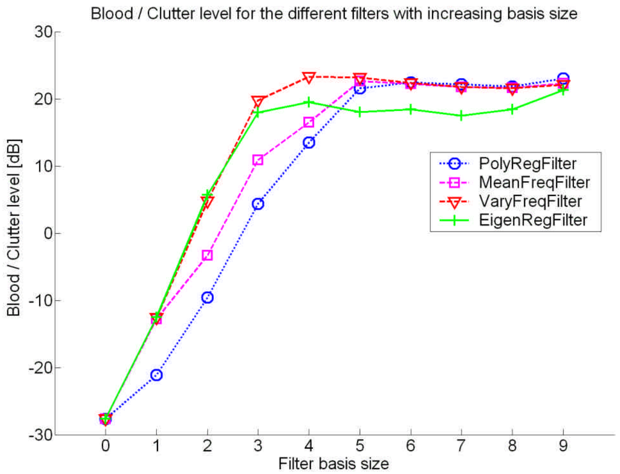
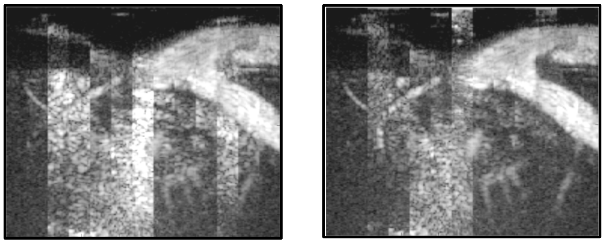
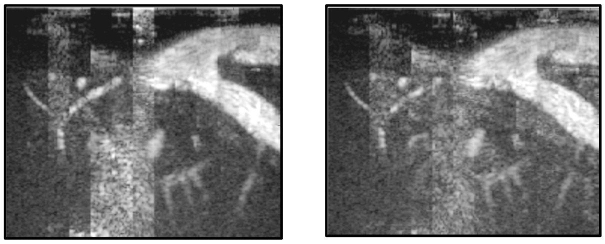


Figure 6: Filter performance in a representative region of accelerated clutter movement, measured in blood-to-clutter level against filter basis size

Gray-scaled amplitude images of the filter output are shown in Figure 7. The filter basis size of three was used in this example. The images clearly show an improvement in reduction of tissue flashing artefacts using the adaptive filters.



a) PR Filter b) MF Filter



c) VF Filter d) ER Filter

Figure 7: Gray-scaled amplitude images of filter output using a) PR, b) MF, c) VF, and d) ER filter respectively, with a filter basis size of three

As a negative side, the eigenvector regression filter has considerably higher computational demands compared to the other filters due to the eigenvector decomposition needed.

IV. CONCLUSION

In conclusion, all three adaptive filters outperformed the non-adaptive polynomial regression filter used for clutter signal attenuation in the presence of uniform or accelerated clutter movement. For a basis size of one to three the varying frequency and eigenvector regression filter were equally the most effective. For a larger basis the varying frequency filter prevailed. Also considering computational demands, the varying frequency filter should be the overall filter of choice.

V. REFERENCES

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