

Using Phase Information in Ultrasound RF-Signals for Tissue Characterization

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Abstract—Due to many processing steps, the B-mode ultrasound images commonly used for medical diagnosis, contain less information than the original Radio-Frequency (RF) signals received by the ultrasound probe. Moreover, the raw RF-signals contain potentially more information on the investigated tissue. In this work we explore whether phase information of the ultrasound RF-signals can contribute to a better characterization of insonified preterm brain tissue. We use time series of raw RF-signals obtained with a linear probe. Amplitude and phase information are extracted from complex valued demodulated RF-signals and subsequently an envelope image is reconstructed. Then, we analyze the distribution of the phase differences both within the signal and between neighboring signal scan lines and compute the entropy of those phase differences in local neighborhoods. Our initial qualitative results indicate that statistical properties of the phase differences, such as the proposed entropy, bring useful information about the insonified tissue.

Index Terms—Ultrasound, Radio-Frequency signals, Phase information

I. INTRODUCTION

The Radio-Frequency (RF) signal is the unprocessed electrical signal coming from the ultrasound scanner's probe. It thus contains all the information on the propagation of the acoustic waves and their intersections with the scanned tissue. The B-mode ultrasound image, displayed on the scanner screen, is a brightness gray-scale image that represents the envelope of the RF signals. Such an image is obtained by demodulating the RF signals. Note that before the image is actually displayed, several processing steps are applied like time-gain compensation, filtering, rectification and log-compression.

Because these steps differ on each ultrasound device, images taken with different machines are difficult to compare. Due to these processing, the loss of information disables us to take full advantage of the received signal in terms of signal processing and automatic diagnoses.

In recent years there have been many studies in the field of ultrasound tissue characterization using unprocessed RF signals, which are recognized as a rich source of information [1]-[5], [8], [11]. However, the main difficulty in ultrasound RF-signal processing is the fact that the interaction between tissue and sound waves is poorly understood. Little is known

on how changes in tissue characteristics influence the reflected signal. Most of the existing works in this area address statistical properties of the RF-signals and envelope images [1]-[4]. Also, little analysis of the phase properties in ultrasound images has appeared, mostly because of the random nature of the phase information.

In this paper we show that, even though the phase information is mostly randomly distributed, there exist correlations between neighboring RF-signal samples that can be used for tissue characterization. We propose the entropy of the phase difference as a statistical measure for the phase correlation and investigate its relation to the amplitude information.

The paper is organized as follows: Section II presents materials and methods that are used in this paper. Firstly, the experimental set-up of the RF-signal acquisition is discussed. Secondly, the demodulation of the RF signals and the image reconstruction process is explained. Next, we briefly describe the entropy calculation of the phase difference. In section III results are displayed together with the visualization of the fused envelope (amplitude) and entropy image using the HSV color space and a discussion is given. Finally, the conclusion is presented in section IV.

II. MATERIALS AND METHODS

A. Experimental data

For the ultrasound data collection we use a Picus ultrasound machine (ESAOTE NV, Maastricht) that contains an integrated PC and the capability of collecting and recording raw RF-signals. These signals are acquired with the Art.Lab software equipped with a data acquisition card, where each acquisition sample consists of 16 bits with the upper 12 bits used for RF-samples and lower 4 bits used for event coding, e.g. trigger signals. We use a linear ultrasound probe (type L10-5 40mm) which supports 5/7.5/10 MHz frequencies. Acquired RF-signals are sampled according to their frequency content, i.e. three to four times the dominant carrier frequency and afterwards stored in real-time in the internal memory of a personal computer system as an RF-matrix. The time interval of the RF-matrix depends on the Pulse Repetition Frequency (PRF) of the probe ($\Delta t = 1/\text{PRF}$), while the depth interval

of the RF-matrix is directly related to the sample frequency f_s ($\Delta y = c/(2f_s)$).

In our experiments the dimension of the RF-matrix is 1532×127 , containing 127 A-lines (RF-signals) with the length of 35 mm, sampled in 1532 points. The sample frequency is 34 MHz and depth interval is $22.82 \mu\text{m}$. The PRF for the used linear probe in B-mode imaging is 3.81 MHz and the time interval between two consecutive RF-signals is $260 \mu\text{s}$, which means that the acquisition of one image takes about 33 ms (Fig. 1).

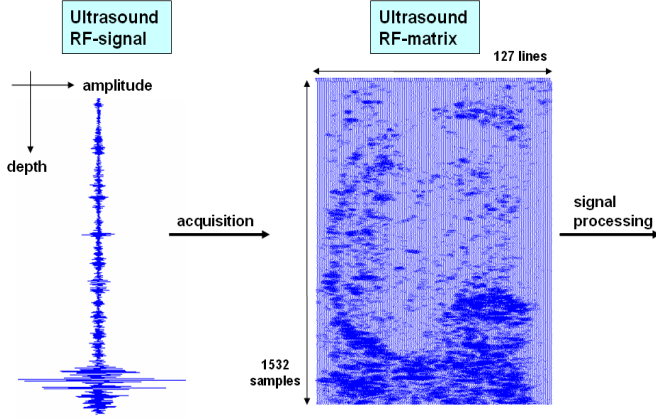


Figure 1. Data storage of the acquired RF-signals in an RF-matrix. RF-samples are organized in depth (top to bottom) and time (left to right).

For the experimental data we have acquired and reconstructed ultrasound images from five different areas of the premature baby's brain tissue: a high coronal section, left and right dorsal ganglia and left and right subcortex. Each set of the images contains a volume of 180 frames of the same tissue obtained by consecutive scanning.

B. Demodulation and image reconstruction

After acquisition, normally the image reconstruction process is preformed and the RF-data, shown in Fig. 1, are reconstructed into a grayscale image. The main step is a demodulation process where the phase information is extracted and the signal envelope detected.

Demodulation is the process of recovering a baseband signal from an analog signal that is modulated at a given frequency. Let $x(t) = \alpha(t) \cos[2\pi f_c t + \varphi(t)] + \alpha(t) \sin[2\pi f_c t + \varphi(t)]$ denote a modulated signal, where f_c is the carrier frequency and $\alpha(t)$, $\varphi(t)$ are the amplitude and the phase functions, respectively. The complex representation of the $x(t)$ is:

$$x(t) = A(t)e^{j2\pi(f_c t + \varphi(t))} = c(t)e^{j2\pi f_c t},$$

where $c(t) = A(t)e^{j\varphi(t)}$ is a complex function, often called the complex envelope of the signal, which combines the amplitude $A(t)$ and phase $\varphi(t)$ information of the signal. In our case, we acquire the real modulated RF-signals by the ultrasound transducer $s(t) = \text{Re}\{x(t)\} = \alpha(t) \cos[2\pi f_c t + \varphi(t)]$.

In order to obtain the complex function $c(t)$ and eliminate the carrier frequency f_c from the signal $s(t)$, we use the Fourier transform:

$$S(f) = \mathcal{F}\{s(t)\} = \int_{-\infty}^{\infty} s(t)e^{-j2\pi f t} dt,$$

to get the frequency domain representation of the original function. The obtained frequency spectrum of the complex envelope $C(f)$ is the shifted spectrum of the signal with the carrier frequency removed:

$$C(f) = S(f - f_c)G(f - f_c),$$

where a bandpass filter $G(f - f_c)$ is applied to $S(f - f_c)$ to reduce the influence of noise. Then the complex envelope $c(t)$ is obtained as the inverse Fourier transform of $C(f)$:

$$c(t) = \mathcal{F}^{-1}\{C(f)\} = \int_{-\infty}^{\infty} C(f)e^{j2\pi f t} df,$$

$$c(t) = A(t)e^{j\varphi(t)}.$$

The envelope and the phase of the RF-signal $s(t)$ are respectively the amplitude $A(t)$ and the phase $\varphi(t)$ of the complex envelope $c(t)$.

Finally, the detected envelope is compressed logarithmically and normalized in order to distribute the gray levels more uniformly and to enhance the image visualization. An example is shown in Fig. 3b), where high amplitude, corresponding to a strong reflection, is represented by a white pixel, while a black pixel indicates small amplitude and no reflection at all.

C. Statistical properties of the phase

Once the amplitude (envelope) image is obtained and the phase is extracted, we analyze the distribution of the phase difference by calculating its entropy in local neighborhoods. We observe the statistical properties of the phase difference, because the pure phase information can be mostly regarded as a uniformly distributed random variable and is hence very difficult to analyze. However, the phase difference we believe to be locally correlated.

We compute the phase difference $\Delta\varphi$ in two different directions: within one signal line (in axial direction) and between two neighbor signals (in lateral direction) in the following way:

$$c_1 c_2^* = A_1 A_2 e^{j(\varphi_1 - \varphi_2)} = A e^{j(\Delta\varphi)}$$

where $c_1 = A_1 e^{j\varphi_1}$ and $c_2 = A_2 e^{j\varphi_2}$ are two different samples (either from the same signal or two different signals) with the amplitudes A_1 , A_2 and phases φ_1 , φ_2 respectively and c_2^* is complex conjugate of the c_2 .

The phase takes on values in the 0° to 360° range and could thus wrap from 360° back down to 0° (meaning that when the phase exceeds 360° it returns to its minimum value 0°) and

vice-versa. In order to have no wrapping, the phase difference is computed as follows:

$$\Delta\varphi = \min_{k-l} |\alpha - \beta + (k-l)2\pi|$$

assuming that the phases $\varphi_1 = \alpha + 2\pi k$ and $\varphi_2 = \beta + 2\pi l$ are small.

Calculating the phase difference we create a new data matrix and compute its entropy in the local neighborhood. The entropy, which is a statistical measure of randomness and system disorganization, is obtained in the following way:

$$E(\Delta\varphi) = - \sum_{i=1}^N p((\Delta\varphi)_i) \log p((\Delta\varphi)_i),$$

where $E(\Delta\varphi)$ is an entropy, $\Delta\varphi = \{(\Delta\varphi)_1, \dots, (\Delta\varphi)_N\}$ is a set of random phenomenon (phase differences), where $N = n^2$ is a number of phase differences in local n -by- n neighborhood (e.g. in the case of a 9-by-9 neighborhood $N = 81$) and $p(\Delta\varphi_i)$ is a probability density function (PDF) of the phase differences. The PDF is empirically estimated as a histogram of the phase differences for each local n -by- n neighborhood. Then the entropy image is reconstructed representing the phase information.

At the end, the entropy image is fused with the amplitude image using the HSV (Hue Saturation Value) color space, for better visualization and comparison of the information. In the HSV color space, the hue (H) represents the entropy of the phase difference (phase information), the saturation (S) is maximum ($S=1$) and the value (V) is amplitude information (the areas where the amplitude information is small are not of interest). The hue colorbar goes from blue to red, where blue corresponds to low entropy and red to high entropy. The outline of our algorithm is shown in Fig. 2.

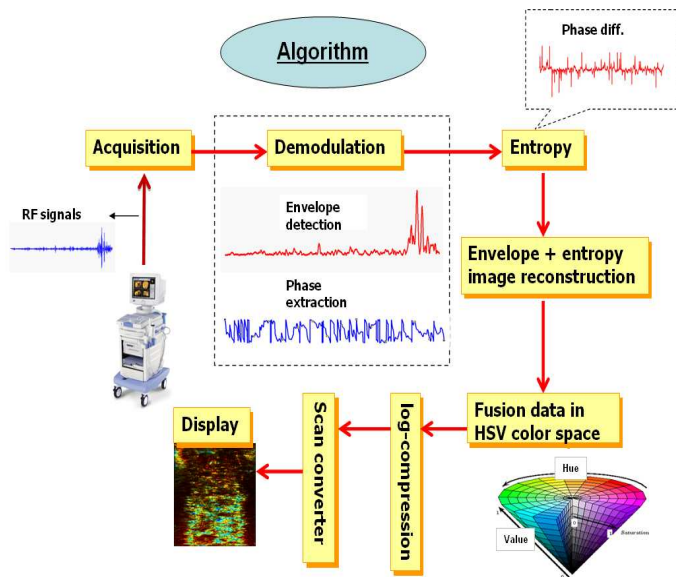


Figure 2. Algorithm of the proposed method for analyzing US images

III. EXPERIMENTAL RESULTS AND DISCUSSION

For experimental purposes, we have reconstructed the amplitude and entropy images from the raw RF-signals sequences of the five different neonate's brain regions (see section II-A). For the local entropy of the phase differences we use a 9-by-9 neighborhood around the corresponding element in the input phase difference matrix. The neighborhood should be big enough (in our case 81) because of the histogram and PDF calculation (see section II-C) that we use for the entropy estimation. On the other hand, if the neighborhood is chosen too big then we could lose the local tissue information.

Fig. 3 shows an amplitude and entropy image together with the HSV representation.

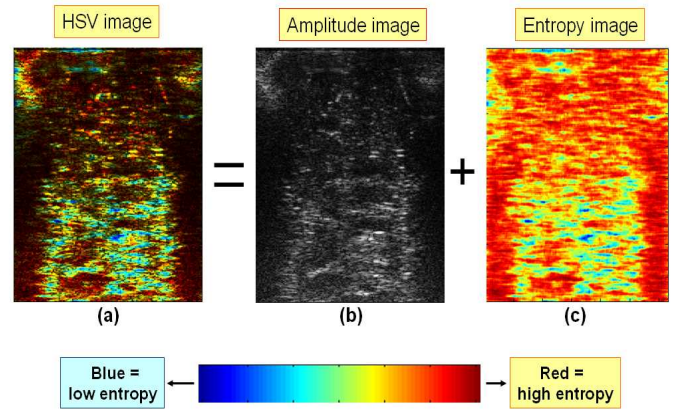


Figure 3. Reconstructed images where: (a) represents the complex valued HSV image (Hue is entropy of the phase difference in 9x9 neighborhoods and Value is envelope image), (b) shows the gray scale envelope image and (c) is the entropy image. At the bottom is entropy colorbar.

In order to discover the potential new information that the phase difference brings, we investigate the correlation between the amplitude image and the entropy-of-phase-difference image. To this end, firstly we compute the phase difference between nearest neighbors and then between non-neighboring samples (every second sample, third sample, etc.), both in the axial (one scan line) and the lateral (two different scan lines) direction.

The obtained results, for the phase difference computed between nearest neighbors, indicate that in the areas of strong tissue reflections there is a noticeable correlation in the phase and envelope information. Also, there are some areas with zero and negative linear correlation that could bring additional information. Furthermore, the correlation is a little bit higher if the phase difference is calculated in the lateral direction.

In the case when the phase difference is calculated between non-neighboring samples, we obtain that the correlation decreases when neighboring samples are further apart. If we do not expect any selfsimilarity or repetition structures to appear, this result has sense, but still has to be investigated for the real tissue. The results are given in Fig. 4.

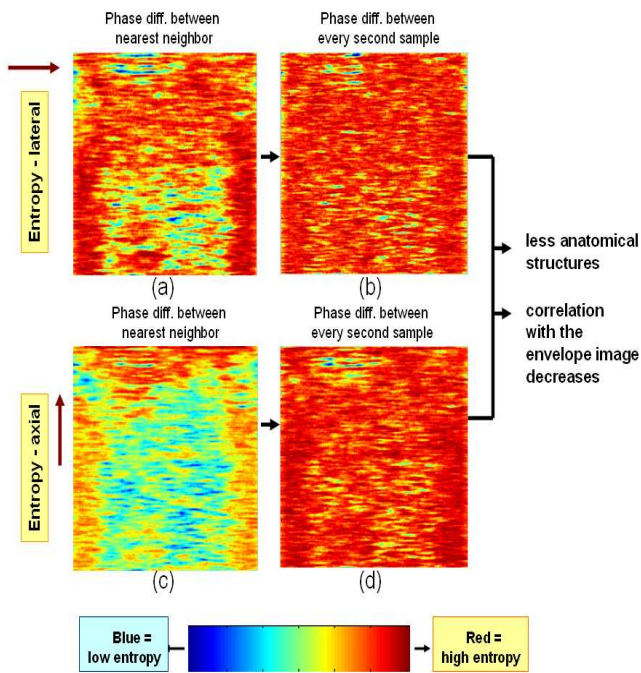


Figure 4. Entropy images are shown where: (a) the phase difference is calculated between nearest neighbors in lateral direction, (b) the phase diff. is calculated between every second sample in lateral direction, and in (c) and (d) example the phase diff. is calculated in axial direction between nearest and second sample respectively.

Applying our method, we also noticed that in most of the cases where amplitude corresponds to diffuse scattering, the phase difference is randomly distributed and the entropy is high. Also, if amplitude indicates that a tissue structure is present, the entropy is low and the phase difference is close to zero. However, we also notice some deviations from the above mentioned amplitude/phase correlation. These distinctions could indicate additional information about the tissue, e.g. like better characterization of the scatters and speckle noise. Visualizations of the described results are illustrated in Fig. 5, where the blue color indicates low entropy and red color high entropy.

IV. CONCLUSION

The initial results of this study indicate, however qualitatively, that the statistical properties of the phase extracted from the raw RF-signals, could identify anatomical tissue structures. It now remains to be investigated whether they also bring some additional, as compared to the regular B-mode image, and useful information on insonified tissue. We plan to continue the qualitative exploration and test our ideas on phantom data where ground truth information on the insonified structures can be controlled.

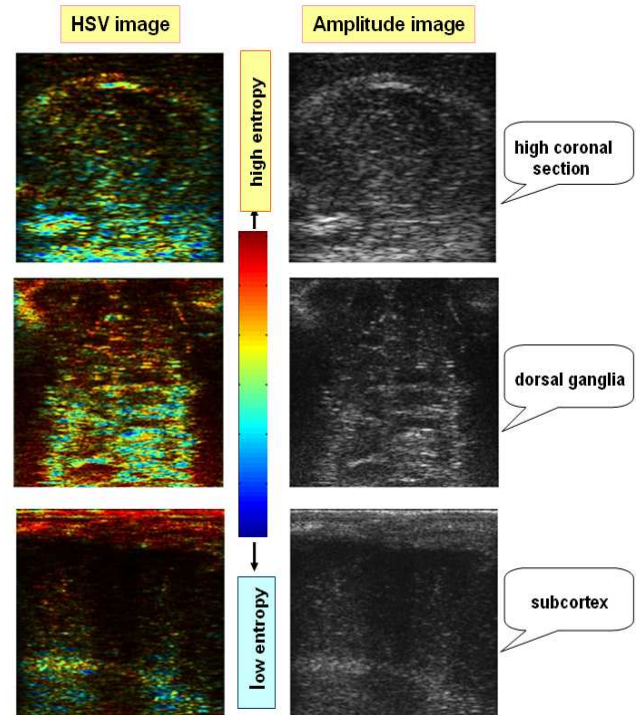


Figure 5. The left column represents complex valued HSV images (Hue is entropy of the phase difference in 9x9 neighborhoods and Value is envelope image). The right column shows the reconstructed gray scale envelope images.

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