RESOLUTION IMPROVEMENT OF ULTRASOUND IMAGES USING DECONVOLUTION AND SUPER-RESOLUTION ALGORITHMS

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Abstract: Ultrasound imaging is a wide spread technique used to view body soft tissues, like tendons, muscle or internal organs for possible problems. These images are achieved by capturing the returned acoustic waves using an ultrasonic transducer. Due to the propagation in imperfect environment, the resolution of these images has a poor quality. This is caused by different problems like waves refraction, attenuations in tissues, destructive waves, bad contacts, and so on. This paper intends to achieve a preliminary synthesis of the most important directions of study for the resolution improvement. We present two important methods for ultrasound image processing: deconvolution based and super-resolution algorithms. Some simulation results are also delivered.

Keywords: *ultrasound, medical image, super-resolution, deconvolution, digital image processing.*

I. INTRODUCTION

The medical diagnostic using ultrasounds became intensive used since the early 1980s, but scanner cost and spatial dimensions has limited its use to hospital settings for decades [1]. From the middle of 1990s, several manufacturers offered portables ultrasound machines, inexpensive, which made increase the presence of this diagnostic method in the world [2].

Ultrasound imaging is a non-invasive medical imaging technique for diagnose. It is used to visualize many internal organs, to capture their size, structure and pathological details. It is also inexpensive compared to others modalities and easy to implement.

The ultrasound image is obtained using ultrasonic waves in 3 to 20 MHz range [3]. These waves, which travel inside the body, are generated using a piezoelectric material able to generate acoustic waves commanded by electrical impulses. When the waves find a contact zone between two different physical characteristics regions, these are reflected and then captured by the transducer. The scanner measures, thanks to a probe, the absolute value of them. In the final image, these amplitudes are represented in gray mode, point by point. The strong echo is presented with white color and the absence is shown with black. The final image resolution depends on several parameters such as the transmit signal, the probe bandwidth, the diffraction effects, the signal-to-noise ratio (SNR), contact between transducer and body, etc [4]. Note that the resolution of images is better when we use higher frequencies but, at the same time, limits the penetration.

There are different modes of ultrasound imaging. The most common modes are [3]:

- B-mode – the basic two-dimensional intensity mode;
- M-mode- to measure moving body parts (for instance cardiac movements) from the echoed sound;
- Color mode - pseudo color based on the detected cell motion using Doppler analysis.

Main advantages of ultrasound imaging are [5]:

- it not inserts radiations in body;
- a moderate price;
- excellent for fluid filled cavities;
- real time images.

Nowadays, despite of the technological level, an ultrasound images with good resolution is difficult to obtain. The main problems (which cause a weak resolution) are the result of reflection, refraction and deflection of ultrasound waves from different types of tissues (with different acoustic impedance). This contains, also, some noises, especially speckle noise.

In this paper we make a shortly review for some denoising techniques, and we discuss how this could improve the ultrasound image resolution. The paper is organized as follows: Section 2 presents the problem description of resolution improvement in ultrasound images; in Section 3 we present a short review of algorithms which can be used in resolution improvement: deconvolution based algorithms and superresolution; Section 4 presents the experiment and results, Section 5 is about future work and, in Section 6 conclusions are presented.

II. PROBLEM DESCRIPTION

The ultrasound images are accomplished putting together, line by line, the amplitude of the reflected waves, which are captured by the ultrasound scanner.

In *Figure 1* we show the main steps in ultrasound image acquisition. The first step is the wave generation. This is realized using a piezoelectric transducer [4].

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Directions of the transducers are aligned to focus the ultrasonic waves at different focal lengths along a given scan-line and the transducers are switched on and then off. During the off time, they listen to the wave echoed by the body cells. The intensity at a given focus point is computed as the sum of the sound waves received by all the adjacent transducers listening just after sending the waves focused at that point.

When passing through the human body, a portion of the ultrasound waves get absorbed by the body cells. This absorption will get accumulated and the waves which travel deeper will become weaker and weaker. Other parts of the waves are reflected and captured by the piezoelectric transducer [3], [4], [6].

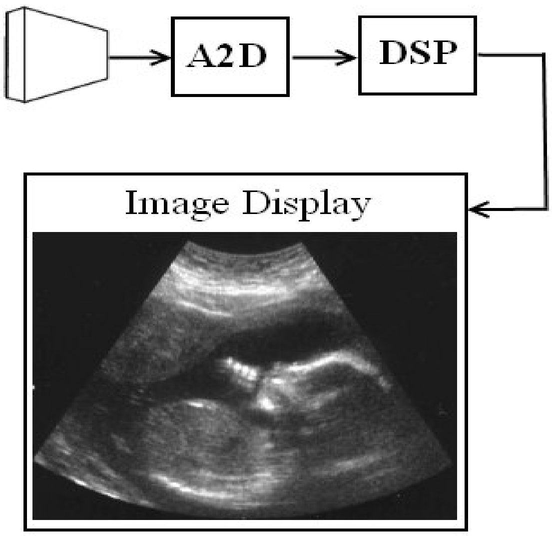

Figure 1. Ultrasound image system acquisition. First step is the capture the echoes. Then, the Analog-to-Digital conversion follows. DSP block achieves the numerical signal processing, where the signal is interpreted and filtrate. The last step is the conversion of signals and their display to the monitor.

These received waves are converted from continuous to discrete domain. The A2D block present in the *Figure 1*, describe the Analog-to-Digital converter. This device is capable to sample input data with a high frequency (order of hundreds of MHz).

After sampling, the resulted information is passed through a series of filters, represented by DSP block (Digital Signal Processing), which process it and extract the useful information. One can enumerate: noise reduction, envelope extraction, logarithmic amplification, etc.

The image display can be made in different modes. The most important are presented in first section of this paper. The most usual is B-Mode, where the received signals, are displayed after filtering and envelope extraction. Usually, the image display depends from the type of the probe (i.e., a planar probe produce a rectangular image, one convex a trapezoidal image) [9].

The noise can be introduced in any stages of acquisition. These noises can be introduced due to the improper contact between probe and body. Another source of bad results can be the signal processing or conversion steps, where some information can be lost.

Now, we will describe the most important type of noise which can affect the information - speckle noise. It is a phenomenon that accompanies all imaging techniques, where images are produced by interfering echo of a transmitted wave, which emanates from heterogeneities of the objects being interrogated. Coming with random phases and amplitudes, the echoes tend to produce an intricate interference pattern, which scales from zero to a maximum, depending on whether the interference is destructive or constructive. In this case, a dark spot, for example, could be interpreted by a medical doctor as corresponding to an area with relatively low reflectivity, which in fact it might be simply caused by echoes compensating each other at opposite phases [7]. In the medical literature, speckle noise is referred as "texture", and may possibly contain useful diagnostic information. The desired grade of speckle smoothing preferably depends on the specialist's knowledge and on the application. For automatic segmentation, sustaining the sharpness of the boundaries between different image regions is usually preferred while smooth out the speckled texture. For visual interpretation, smoothing the texture may be less desirable [8].

III. A SHORT REVIEW OF ALGORITHMS

When we evaluate the quality of an ultrasound image we evaluate in fact, some parameters like the contrast and resolution. In ultrasound medical image the accuracy of the image is accomplished by the type of waves, the geometry of transducer, or by a combination of them. The images are preformed with multiple-element "arrays" of piezoelectric crystals. In [9] we can found a general description for transducer, equivalent circuit transducer model and some examples.

Nowadays, exists more research direction for resolution improvement but the most important remain the deconvolution, super-resolution and time reversal. In the next paragraphs we will present a brief of these methods and the actual stage of research.

Deconvolution

Deconvolution is an algorithm-based process used to reverse the effects of convolution on recorded data. This is useful for analyzing the characteristics of the input signal and the impulse response when only we give the output of the system. For example, when a convolved signal is given, the system should isolate the components and such that we may study each individually.

Most of deconvolution algorithms are implemented in the frequency domain. The most important types of linear deconvolution are [10]:

- Inverse filtering;
- Blind Deconvolution;

- Wiener filtering;
- CLEAN algorithm.

Inverse filter is the simplest and most naïve method for deconvolution. It has effect only in blurred images and the noise is not eliminated.

Typical filters are designed for a desired frequency response. However, the design of the Wiener filter takes a different approach. One is assumed to have knowledge of the spectral properties of the original signal and the noise, and one looks for the linear time-invariant filter whose output would come as close to the original signal as possible. Wiener filters are characterized by the following:

- Assumption: signal and (additive) noise are stationary linear stochastic processes with known spectral characteristics or known autocorrelation and cross-correlation.
- Requirement: the filter must be physically realizable/causal (this requirement can be dropped, resulting in a non-causal solution).
- Performance criterion: minimum mean-square error (MMSE).

In the literature one can find many articles about deconvolution and its results for ultrasound images. In [11], [12], [13] authors realized different comparisons between some linear deconvolution methods. All of them say that best visual results are obtained using a Wiener filter. O. Michailovich and A. Tannenbaum proposed in [14] a new methodology of blind deconvolution which can be viewed like a hybridization of two standards in this procedure. Specifically, they propose to model the inverse transfer function as a member of a principal shift-invariant subspace. It is shown that such a parameterization results in considerably more stable reconstructions as compared to standard parameterization methods.

Besides linear methods presented bellow, some nonlinear methods for deconvolution are available. One of the most important is CLEAN method. It was developed by Hogbom to perform a deconvolution on images created in radio astronomy images. The algorithm assumes that the image consists of a number of point sources. It will iteratively find the highest value in the image and subtract a small gain of this point source convolved with the Point Spread Function (PSF) of the observation, until the highest value is smaller than some threshold [15]. This algorithm is useful because of images formation similarities in both domains.

Super-resolution

Super-resolution is the name of a set of methods used to enhance the resolution of the images. The main idea of super-resolution is to use some low resolution images as references to create a zoomed one with better details. Super-resolution works effectively when several low resolution images contain slightly different perspectives of the same object. Then total information about the object exceeds information from any single frame. The best case is when an object moves in the video. Motion detection and tracking are then employed to benefit upscaling. If an object does not move at all and is identical in all frames, no extra information can be collected. If it moves or transforms too fast, then it looks very different in different frames and it is difficult to use information from one frame in reconstructing the other [16].

There are different types of approaches:

- Non-uniform interpolation;
- Deterministic Approach;
- Stochastic Approach;
- Frequency Domain Approach;
- Projection onto Convex Sets Approach;
- Adaptive Filtering Approach; etc.

The super-resolution algorithm is used with success in close domains. M. Mastriani presents in [17] a novel projection algorithm for speckle removing (in wavelet domain) of unknown variance for Synthetic Aperture Radar (SAR) images. His experimental results demonstrate that the new method works better then several other despeckling methods on this type of images. In the literature we find a small number of papers which describes their applications in ultrasound medical images.

IV. RESULTS AND DISCUTIONS

In this paper we study the effect of above presented methods for ultrasound images resolution improvement. For tests we use different image types: original, blurred or noised. The image presented in this paper has the 414x274 pixels and 8 bit gray levels. In *Figure 2* we show an example. All simulations were implemented in MATLAB and were tested with an Intel I5 processor with 4 GB of RAM.

The blur and the noise for the images were obtained with a Gaussian kernel. Also, initial images had some speckle noise, in an unknown level.

Inverse filtering is the process of recovering the input of a system from its output. Inverse filter is obtained by dividing the degraded image with the original image in the 2D- transform domain. If the degradation has zero or very low values, when we invert these values the result is infinite. To eliminate this inconvenient we make all the values smaller then a threshold equal with it. In our code the threshold value is 0.2.

For blind deconvolution we use the MATLAB implemented function with a 5x5 window size PSF.

Wiener filter is the optimal tradeoff between the inverse filtering and noise smoothing. It can be interpreted as an inverse filtering step followed by a noise attenuation step. For tests we use the MATLAB function with a 5x5 pixels window, because from our previous works it offers us the best results.

The used PSF has a Gaussian beam with 15x15 pixels window size and sigma 1. Also, the loop gain value is 0.1. We choose this value because in typical radio astronomy applications the recommended value is between 0.1 and 0.25.

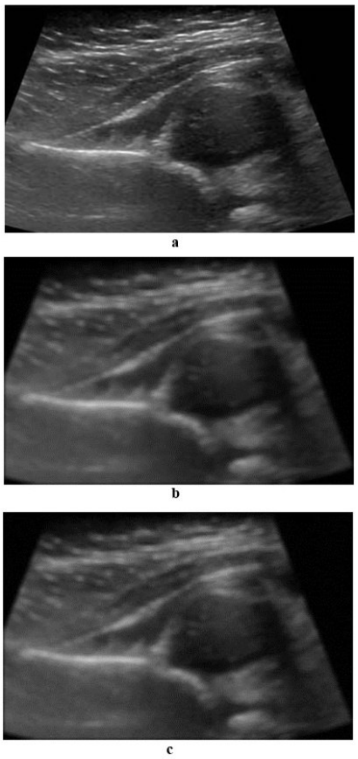

Figure 2. Initial images: a - original image, b - blurred image, c - image with blur and noise.

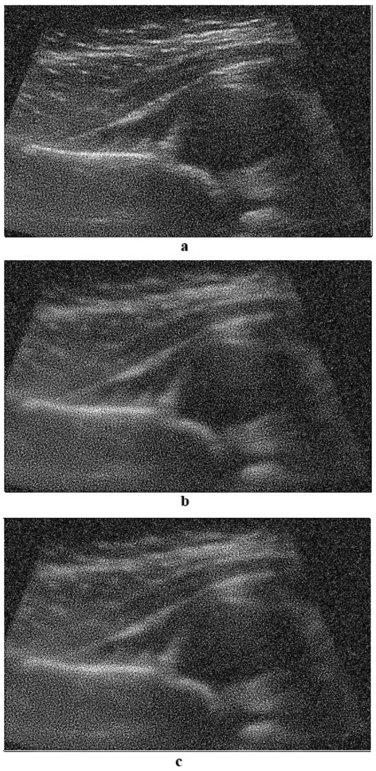

Figure 3. Inverse filtering results for: a - original image, b - image with blur, c - image with blur and noise.

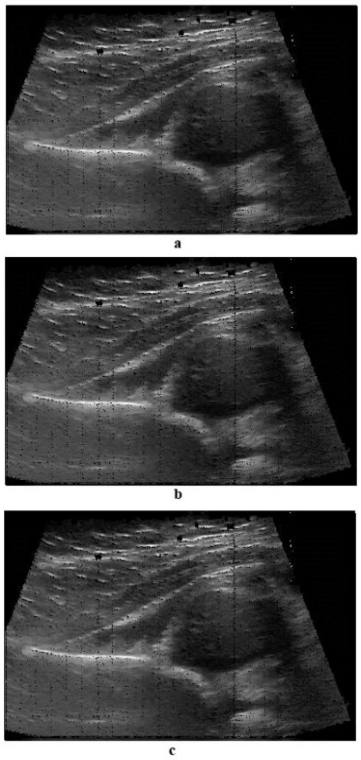

Figure 4. Blind deconvolution results for: a - original image, b - image with blur, c - image with blur and noise.

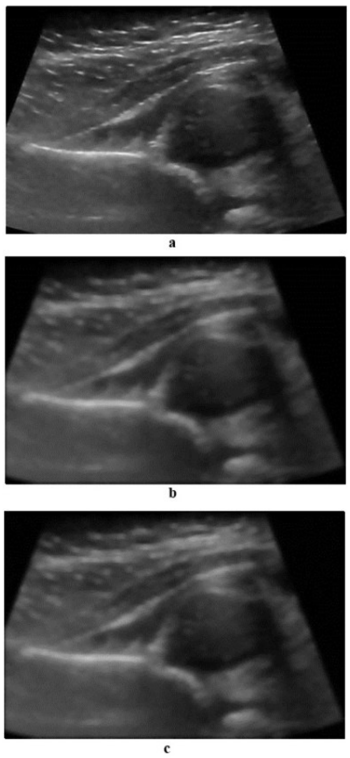

Figure 5. Wiener filtering results for: a - original image, b - image with blur, c - image with blur and noise.

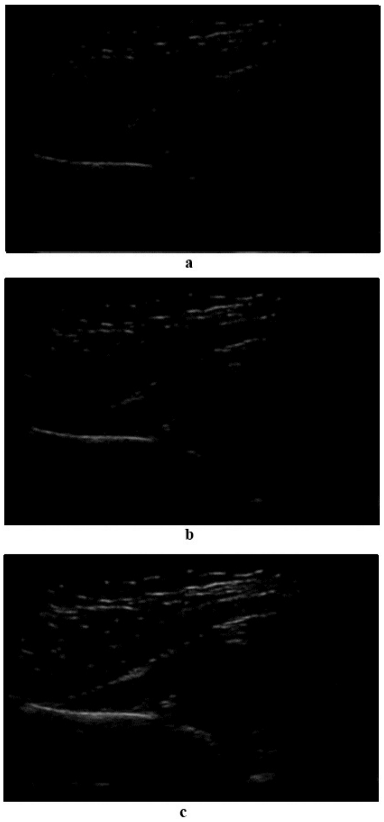

Figure 6. Cleaned map after: a - 70%, b - 60%, c -52% maxima threshold.

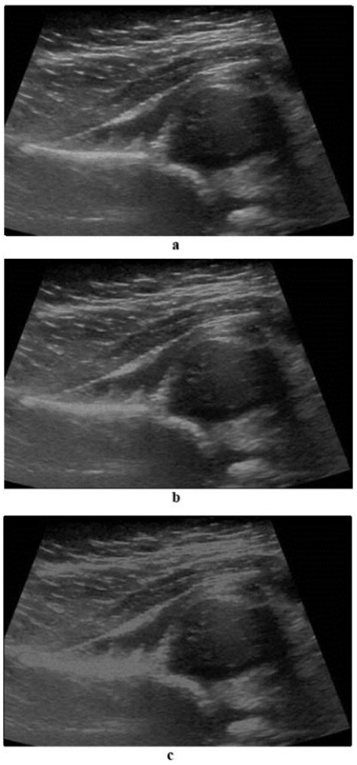

Figure 7. Residual map after: a - 70%, b - 60%, c -52% maxima threshold.

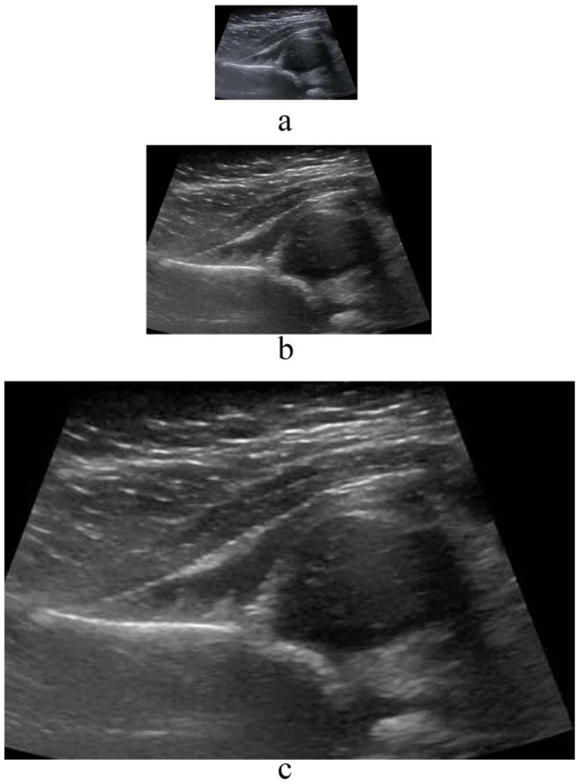

Figure 8. Single image super-resolution: a - initial image, b - 2x resolution, c – 4x resolution.

Threshold [% to max]	70	65	60	55	52
Time [sec.]	97.83	172.05	291.85	394.67	884.57

Table 1. Execution time for different threshold values.

For super-resolution we test a Kernel ridge regression algorithm implemented by K. I. Kim, Y. Kwon in [18]. Kernel Ridge Regression (KRR) is used to estimate the high-frequency details of the underlying high-resolution image. A sparse solution of KRR is found by combining the ideas of kernel matching pursuit and gradient descent, which allows time-complexity to be kept to a moderate level. MATLAB code was developed by authors and we just test it. One can see that inverse filtering has bad results in presence of noise (*Figure 3*).

After simulations we observe that without an *a priori* knowledge of noise spectral density, the images resolution is difficult to obtain. More, the method has an accentuated destructive effect and we lost a lot of information (*Figure 4*).

The best results are obtained with Wiener filter in all situations: with blur, noise and without them (*Figure 5*).

CLEAN algorithm has a different role from the above presented algorithms. It is useful for extracting the punctual brightest object from an image (*Figure 6*).

CLEAN offer us the possibility to extract or determine the size of a scatter like cysts or tumors in a homogenous environment. Its disadvantage is the execution time, which increases exponentially with the threshold diminution (*Table 1*).

In *Figure 8,* we show the results of a single image super-resolution algorithm. One can see that image resolution can be increased with the details preservation.

V. FUTURE WORK

Many problems after this work remain for discussion. In the future work one proposes implementation of other techniques, used in signal processing, to improve the resolution of ultrasound medical images. Optimal commands methods are targeted. The advantage of the optimal methods is that the algorithms have the power to chose the best parameters according to chosen cost function. Also, are indicated some quantitative evaluation methods for their comparison like mean square error (MSE) and signal-to-noise ratio (SNR). Even if a method seems to have, in terms of visual evaluation, an better quality then other, the evaluation parameters can have modest result when evaluates them with numerical criterion.

This paper presents a series of techniques which work with the envelope of the radio-frequency ultrasound signal. One idea for a future work is to obtain the radio frequency signals captured by transducer and to test some specific RF methods to obtain a better accuracy. Also, we want to compare the RF and envelope methods in a quantitative and qualitative to verify the better approach.

VI. CONCLUSIONS

In this paper, we intend to make a short review of the most important techniques in ultrasound image resolution improvement: deconvolution based algorithms and super-resolution.

Deconvolution based algorithms are the most popular ones, faster and easy to implement, but they do not offer a good solution, except for the Wiener filter.

CLEAN algorithm is slower than filtering deconvolution methods, but it can offer us a new approach for ultrasound images. It is also, good for punctual sources in the image. We intend to study other algorithms which have better results for wide sources.

Super-resolution seems to be useful for this domain. Test of the single image super-resolution algorithm show us that are capable to increase the clarity of images and their dimensions.

For future work we intend to implement some optimal methods for make the deconvolution automatically and, also, we want to implement some numerical techniques for evaluate the results.

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