OPTIMIZATION OF MEDICAL ULTRASOUND TRANSDUCERS WITH SIMULATION AND GENETIC ALGORITHMS

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ABSTRACT

In recent years, software systems for the simulation of medical ultrasound imaging have been developed, thus making it possible to partially prototype transducers in software. In this paper a set of ultrasound transducer parameters is optimized using a genetic algorithm (GA). The settings are evaluated by simulating a B-mode scan for each transducer configuration. The quality of the generated B-Mode images is assessed by an image quality metric.

Keywords: ultrasound simulation, genetic algorithms, parameter optimization

1. INTRODUCTION

Ultrasound (US) imaging has become an attractive technology for medical diagnosis due to its non-invasive nature, real-time capability and cost effectiveness. Unlike other diagnostic modalities, ultrasound systems do not emit ionizing radiation and scans may be conducted as often as necessary without the risks of repeated exposure to X-rays or radionuclides.

Unfortunately speckle artifacts and low spatial resolution limit the use of ultrasound imaging in clinical practice. A variety of methods have been proposed to improve US image quality and assist physicians in the interpretation of their scans. One possible approach is the utilization of image and signal processing algorithms to remove artifacts and enhance the contrast (cf. Section 2.2). This is mostly a post-processing step, though, taking over after the image has already been captured.

In this study the focus will be on the medical ultrasound scanner instead, and more specifically on the optimization of the transducer probe. The probe is the part of the ultrasound system that emits the sound waves and receives its echoes. It is therefore most crucial for obtaining high-quality US images.

The authors propose a software-based and fully automatic optimization of transducer arrays in order to improve ultrasound image quality. An ultrasound simulator and a genetic algorithm are employed to achieve this goal (cf. Section 4).

2. DIAGNOSTIC ULTRASOUND IMAGING

In medical ultrasound a sound wave is produced by an array of piezoelectric transducers. To ensure good coupling between patient and ultrasound probe a water-based gel is usually applied to the patient's skin before scanning. The transceiver probe emits a pulse of ultrasound and then switches to reception mode to register the reflected echoes. The reflected or backscattered echoes are detected and used to form a digital image of the scanned region.

2.1. Imaging modes

One of the oldest – and most basic – ultrasound modes is the so-called A-mode scan (abbreviation for amplitude scan). A single ultrasound pulse is emitted from the probe. When the pulse crosses the boundary between two tissues of different density, part of the wave is reflected back towards the probe. This echo is detected by the transceiver and displayed as a spike in a line plot.

Brightness mode (also known as B-mode) images are produced by arranging many A-scans parallel to each other and displaying the amplitudes as grey-scale values. The raw radio-frequency (RF) data compromises both amplitude and phase information from the detected waves, the latter of which is discarded during envelope detection. To display the amplitudes the resulting image has to be compressed, as most computer screens only have a dynamic range of 20-30 dB (Dutt 1995).

Other important imaging modes include M-mode and Doppler sonography. For further information on ultrasound technology and instrumentation see for example (Zagzebski 1996).

2.2. Speckle, Noise and Low Resolution

Both the spatial and contrast resolution of ultrasound B-mode scans are limited by speckle artefacts that give the images their characteristic granular structure (Burckhardt 1978). Speckle is caused by tiny particles below the resolution of the ultrasound modality, also called scatterers, which produce a random interference pattern that has no direct link to the biological structure of the scanned tissue.

Since the speckle pattern obscures biological features, blurs tissue boundaries and restricts the contrast resolution of US images, different techniques have been applied to suppress this undesirable effect, among them spatial compounding (Trahey, Smith and von Ramm 1968) and filtering (Loupas, McDicken and Allen 1989, Jin, Silva and Frery 2004).

Insonifying a patch of tissue from different angles, using different ultrasound transducers or pulse length will produce quite different speckle patterns. However, if an object is scanned twice under exactly the same conditions, an identical pattern is obtained (Burckhardt 1978). That is why speckle patterns, although they appear to be random, are not noise in the same sense as for example electrical noise. It would therefore be interesting (in a subsequent stage) to analyze the produced speckle patterns for a number of transducer arrays and identify possible parameter dependencies.

Apart from presenting potential future work, the speckle patterns also strongly influence the choice of the evaluation function in Section 4.4.

3. PREVIOUS WORK

Researchers have used heuristic optimization algorithms, like genetic or evolutionary algorithms, to optimize or estimate ultrasound transducer settings in the past, albeit mostly with a strong focus on electromechanical design parameters.

Fu, Hemsel and Wallaschek (2006) employed evolutionary algorithms to optimize the setup of Langevin ultrasound transducers, also called sandwich transducers. The name is due to their characteristic setup, which consists of (multiple) piezoelectric ceramic disks sandwiched between metallic end blocks. Relevant design parameters include the materials used in the different layers, layer thickness or the number of piezoelectric elements. These transducers are developed for industrial machining, especially high vibration welding and cleaning. The optimization objectives (maximize the vibration amplitude; minimize the electric input power) differ significantly from the objectives for a medical ultrasound transducer (maximize the diagnostic value of generated B-scan images; maximize comfort and safety of the patient), as pursued in this work.

Ruíz, Ramos and San Emeterio (2004) addressed the reverse problem in their work, namely how to estimate the internal design parameters (thickness, acoustic impedance etc.) for an existing ultrasound transducer. This is especially useful for modeling and simulation of ultrasound systems, since the construction details of commercial ultrasound probes are rarely known. In this case the transducer is regarded as blackbox and the internal parameters are estimated from the output signal via a genetic algorithm.

4. A SYSTEM FOR THE OPTIMIZATION OF ULTRASOUND TRANSDUCER SETTINGS

The proposed system consists of the following modules, which will be explained in detail after the general overview of the algorithm:

- **HeuristicLab:** Optimization Framework
- **Field II:** Ultrasound Simulator
- **Image Quality Index** (IQ): Similarity measure between two images

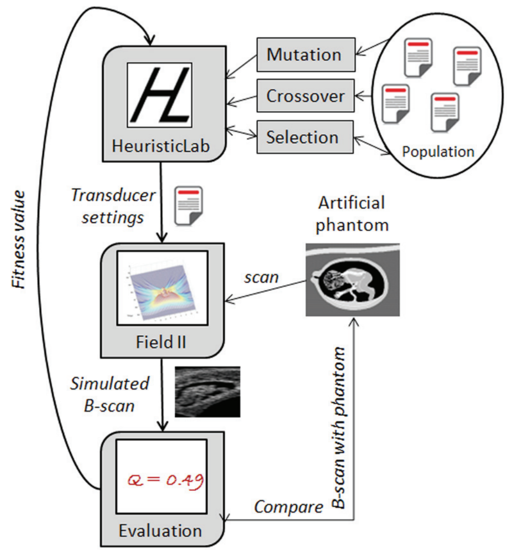


Figure 1: Fully automated optimization cycle

The heuristic optimization environment HeuristicLab provides all the necessary components to build a customized genetic algorithm (Holland, 1992) for the optimization of transducer parameters.

A single transducer is represented by a vector of real values containing parameters such as the center frequency or the number of sensor elements (for a detailed list of the selected parameters see Section 4.2).

As depicted in Figure 1 the optimization cycle works in the following way:

1. Initially HeuristicLab generates a number of vectors (= transducers) which are randomly initialized. In order to generate (preferably better) offspring from this initial population, the quality, also called fitness, of the available transducers has to be assessed first.
2. The parameter vectors are therefore passed on to the ultrasound simulator Field II which simulates a B-mode scan with each transducer and produces an image.
3. This scan is then evaluated by the Image Quality Index module which assigns a fitness value between 0 and 1 to the image (and thus indirectly determines the quality of the transducer).

4. Our GA commences with the usual optimization steps (parent selection, generate new individuals with crossover/mutation, evaluation of new transducers, replacement mechanism etc.).
5. The algorithm terminates after a pre-defined number of iterations or in case of manual abortion of the optimization.

4.1. HeuristicLab

HeuristicLab (Wagner et al. 2007) is a paradigm-independent and highly customizable optimization framework. HeuristicLab provides a number of standard workbenches for frequently used algorithms, but its plug-in based architecture allows users to integrate their own problem representations or domain-specific operators into the system with ease.

4.2. Simulation with Field II

The ultrasound simulation program Field II (Jensen and Svendsen 1992, Jensen 1996) by Jørgen Ardendt Jensen from the Technical University of Denmark was used as simulator in this study. Field II relies on linear system theory to model the ultrasound field emitted from the transducer. In ultrasound imaging the impulse response varies in relation to the position relative to the transducer, hence the name spatial impulse response. Field II can approximate the spatial impulse response for arbitrary transducer settings and geometries.

4.3. Parameters for optimization

Field II simulates ultrasound transducers of arbitrary shape and facilitates an assortment of custom parameter settings, including dynamic focusing and apodization (= reduced vibration of the transducer surface with distance from its center), different excitation pulses, concave and even sparsely populated transducer arrays (Jensen 1996).

For this study the parameters subject to the optimization were limited to a selected few, namely:

- **f0**: Transducer center frequency
  Range: 2.5 – 15MHz
  A higher frequency generates a focused ultrasound beam that yields better image resolution at the cost of reduced imaging depth.
- **fs:** Sampling frequency
  Range: 0–200 MHz
- **element_height:** Height of one element
  Range: 0-10 mm
- **element_width:** Width of one element
  Range: 0.1-1 mm
- **kerf:** Spacing between elements in lateral direction
  Range: 0.1-5 mm
- **focus:** Fixed focal point (*lateral, elevational, axial*)
  At the focal point the sound field constructively converges. The focal point is given relative to the center of the transducer surface which is defined as (0,0,0). The axial location, also called the focal depth, is of particular interest.
  Range (for axial location): 0-100 mm
- **n_elements:** Number of physical elements in lateral direction (= one-dimensional array)
  Possible Values: 2, 4, 8, 16, 32, 64, 128, 256, 512 and 1024

Figure 2 shows the physical dimensions of a transducer and its main parameters (except for the transducer frequency). Each setting of the parameter vector *(f0, fs, element_height, element_width, kerf, focus, n_elements)* describes an individual ultrasound transducer and serves as representation of a solution candidate for the genetic algorithm The quality of each GA-generated solution candidate is assessed by simulation of the transducer with Field II and subsequent evaluation of the generated ultrasound B-mode image (cf. Section 4.5).

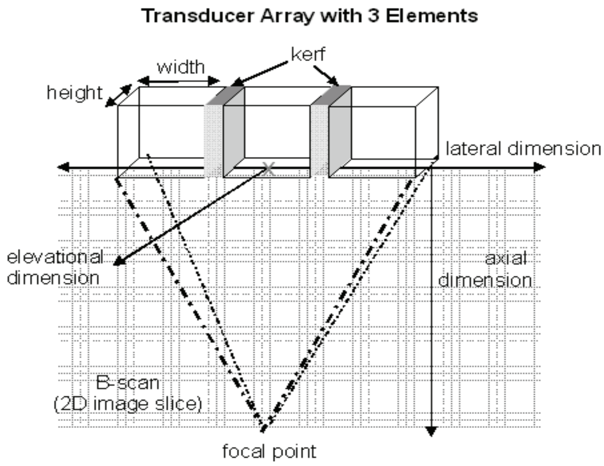


Figure 2: Transducer parameters and nomenclature for the ultrasound imaging directions (axial, lateral, elevational).

4.4. Simulating a B-mode scan

To assess the quality of ultrasound transducers a variety of clinical requirements has been identified by Angelsen et al. (1995), among them spatial resolution, imaging artefacts and sensitivity. In addition, anatomical constraints, as encountered in the fields of cardiac or pelvic ultrasound, and patient comfort may pose restrictions on both the size and shape of the transducer probe. For example, to scan the chambers and valves of the heart the ultrasound beam has to be aimed through a narrow opening between the ribs, since both bone and lung tissue obstruct the passage of ultrasound waves. Transthoracic transducer probes are therefore usually narrow and long. Similar restrictions apply for gynecological exams, breast ultrasound screenings or transrectal exams.

Such application specific considerations aside, a medical ultrasound system is mostly judged by the quality – in terms of diagnostic value – of the ultrasound images it produces. Therefore the authors decided not use physical target parameters (like the vibration amplitude) to evaluate transducers but to perform an examination on a “virtual patient” and rate the transducers by the image quality they produce.

A synthetic phantom of a fetus in the third month of development (Jensen and Munk 1997) was used for the evaluation of the transducer setting (cf. Figure 3). For each generated transducer array a scan of the phantom was simulated with Field II. One image scan consists of 128 raw radio-frequency (RF) lines that can be calculated in parallel to speed up the simulation. The generated RF-data was then post-processed for display on a computer screen by discarding the phase information and performing logarithmic compression, thus yielding a simulated B-mode scan of the phantom.

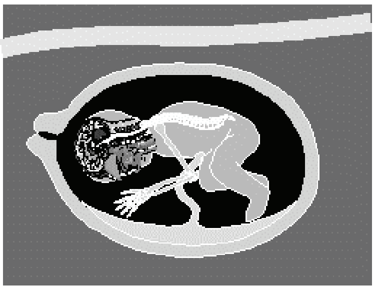


Figure 3: Synthetic phantom of a fetus in the third month of development (Jensen and Munk 1997): The varying grayscale values depict the scattering strength and density of the modeled tissues. The phantom is generated with 200.000 randomly distributed scatterers.

The evaluation of B-mode images is usually performed by human experts. While this is certainly the most accurate and important method of assessing image quality for medical diagnosis, the generated images were rated by employing the image quality index (IQ) proposed by Wang and Bovik (2002) to create a fully automatic optimization cycle as depicted in Figure 1.

4.5. Image quality index

The grainy appearance of ultrasound B-mode images is not only a diagnostic issue but also makes image processing very difficult. As reported by (Pluim, Maintz and Viergever 2003) it is often necessary to smooth the ultrasound images (e.g. by low-pass filtering) before common medical image processing algorithms for feature detection or registration can be applied.

The image quality index was selected for fitness evaluation because it works well under different kinds of image distortions, including multiplicative speckle noise (Wang and Bovik 2002). The method takes the phantom image and the generated image and calculates a similarity measure scaled between 0 and 1.

5. RESULTS AND DISCUSSION

A standard GA with a population size of 10 individuals was used to test the optimization concept. The initial population was generated with a random parameter setting. Due to the long simulation times, especially for transducers with large *n_elements*, the algorithm completed three iterations and produced a total of 43 transducer settings that were evaluated so far. Two aspects have affected the optimization test run severely, namely

- simulation time requirements and
- issues with the image quality index IQ

which shall be elaborated in more detail in the following sections.

5.1. Simulation time requirements

Simulating a single RF line took 25 minutes on average on a Pentium 4 CPU, 3GHz with 1GB RAM. Since one generated B-mode image consists of 128 such lines, simulations were conducted in parallel on 10 Pentium 4 computers to reduce the total processing time.

Despite the parallelization of the ultrasound simulation, evaluating a single population of transducer parameter settings can take a couple of days, thus the number of individuals per generation was limited to 10. The processing time per RF line ranged between 20 seconds and 14 hours, depending on the individual parameter settings. Experiments with 1024 *n_elements* were tried as well but proved to have a very unfavorable simulation time (approximately 1 week per B-mode image, with parallel simulation on 10 workstations).

The authors expect that transducer setting with larger *n_elements* will dominate the optimization as the number of iterations increases, thereby requiring more and more processing time for the evaluation. The currently available parallel infrastructure with 10 desktop computers, which can be utilized for nightly evaluation runs, is not sufficiently dimensioned to complete such a task within an acceptable time span. An anticipated expansion of our simulation cluster will improve the scaling of the algorithm for transducers with large *n_elements*, thus alleviating the issue of increasing simulation times.

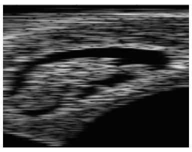
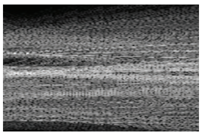
Alternatively, since the RF lines can be simulated independently of each other, one could define a region of interest (ROI) of perhaps 20 lines which are simulated first in case of a large *n_elements* value. Subsequently the fitness of the ROI is calculated and used to assess whether the simulation of the whole image would pay off or if that particular parameter set should be discarded immediately.

5.2. Fitness evaluation

To get a better appraisal for the fitness values of the generated transducers a reference fitness value from a transducer that was known to be feasible was needed.
The authors used Jensen and Munk’s (1997) original parameter settings from the paper to generate the B-mode image that is displayed in Table 1 as #1. The fitness value of 0.552 shows the impact the presence of speckle has on image-similarity, even for parameter settings that are surely very good.

As described in Section 4.5 the image quality index IQ does indeed work well despite the presence of speckle patterns in the generated images. What the authors had not anticipated were the spatial deformations of the target B-scan (see Table 1, #2) that were produced by some of the settings. Since the image quality index was not designed to do registration of medical US images as well, this led to IQ rankings that did not sustain a visual inspection, as in the case of scan #2 and #3 in Table 1. A further refinement of the fitness evaluation is therefore defenitely adviseable.

Table 1: Parameter settings for selected transducers, their respective simulated B-scans and fitness values. The elements of the parameter vector and their units are (f0[MHz], fs[MHz], element_height[mm], element_width[mm], kerf[mm], focus[mm], n_elements)

#1 	Reference Configuration (Jensen and Munk 1997): Settings: (5, 100,7, 0.308, 2.5, 70, 64) **F = 0.552**
#2 	Good solution from GA Settings: (7.379, 129.005, 4.81, 1.263, 0.199, 81.31, 64) **F = 0.432**
#3 	Bad solution from GA Settings: (4.327, 155.42, 0.933, 6.187, 0.5327, 40.679, 16) **F = 0.49**
#4 	Worst simulated solution Settings: (12.77, 12.16, 0.558, 4.529, 0.667, 90.993, 256) **F = 0.0827**

6. CONCLUSION AND FUTURE PERSPECTIVES

The authors showed that it is possible to optimize medical ultrasound transducer arrays autonomously using a genetic algorithm, an ultrasound simulation program and an image quality metric. The main issues of the approach in its current form are the duration of the simulation runs and an image quality metric that is still far from optimal.

Nevertheless, the authors are convinced that the optimization of ultrasound transducers via simulation and genetic algorithms might be an attractive option for ultrasound manufacturers to reduce their hardware prototyping efforts. Since the algorithm works autonomously, it could schedule the RF-line calculations to run on unoccupied desktop computers during the night and/or on weekends, and calculate a pre-selection of promising transducer geometries for subsequent hardware prototyping and clinical tests.

By extending the parameter set, e.g. by allowing sparsely populated arrays, even new transducer geometries might be found – always assuming that the simulation yields valid results for unusual settings. The authors plan to consult ultrasound experts in the next development step to discuss the simulation results and to further refine both the image quality index and the parameter set for optimization.

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