Chapter 13
Implementation of an FPGA Real-Time Configurable System for Enhancement of Lung and Heart Images

K. B. Sowmya, T. S. Rakshak Udupa, and Shashank K. Holla

13.1 Introduction

Field-programmable gate arrays (FPGAs) are no longer challenging to use as logic arrangements, and they comprise the backbone of softcore processors [1, 2]. By softcore processor, the authors mean a software-defined microprocessor synthesizable in programmable hardware. Currently, they permit software designs with reconfigurable hardware platforms in terms of both logic wiring and algorithms. The fine-grained nature of FPGAs facilitates the parallelization, reconfigurability, and programmability of the system.

Regrettably, FPGAs may pose some caveats when it comes to practical programming. Hardware architectures with a fixed computational design, on the other hand, entail a high level of thought due to the need to respect architectural limitations. Therefore, an FPGA needs algorithms and the computational structures leading to a design that explores and conciliates several complexity levels. This fact, together with the complications of dealing with flexible parallel schemes and the extreme bandwidth concerns stemming from the high data volume related to images/video, resulted in a wide range of FPGA-based realizations for image processing systems.

This manuscript discusses how to implement and improve the real-time configurable system for image enhancement using the Verilog Hardware Description Language (HDL).

Image processing is used in various fields of modern society and especially in medical imaging and, recently, assists in the diagnosis of diseases. Image processing is a vast field that employs rigorous mathematical theory. Nowadays, image processing is an emerging biomedical tool that helps in the advancement of the healthcare sector. Recent image processing tools can perform image analysis, image

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enhancement, noise reduction, image segmentation, geometric transformations, and image restoration.

Many motives give rise to blurry images. The finite size of the X-ray source focal spot and, therefore, the detector element within the computer tomography (CT) array, the imaging system owns an imperfect resolution, and image data lost throughout the image acquisition. Enhancements in imaging technology and algorithms have increased the clarity of medical images and contributed to a better diagnosis. Diminishing the blur enhances the overall picture quality.

The proposed arrangement is suited for various images. Different techniques we followed allow better tuning for threshold amount and less iteration involved in the enhancement process, causing faster, more efficient, and more accurate results. Our prototype consists of five enhancement stages that operate independently and without any interdependencies.

In Sect. 13.2 of this text, there is a literature review. The suggested methodology appears in Sect. 13.3. Section 13.4 shows the experimental results. Section 13.5 addresses some future ameliorations in the recommended framework, and, to finish, conclusions appear in Sect. 13.6.

13.2 Literature Survey

As image sizes and bit depths grow larger, software faces more challenges, and real-time hardware systems are options to achieve better results [3]. The planning and, consequently, the implementation of real-time hardware enhancements to speed up image processing for biomedical in the spatial domain on FPGA appear in [4]. A hardware design based on FPGA appears in [3] for image filtering. Contrast enhancement techniques allow displaying the details that are present in the lower dynamic range of the image. Operations like contrast enhancement and reduction or removal of noise improve the quality of the image. The local mean filter smoothes the image by taking the mean value of the pixels nearby the center pixel within the picture [5]. Direct application and improvement of the real-time configurable system for image improvement using the Verilog HDL and reconfigurable architecture are delineated in [6]. A comparative study of various enhancement techniques, such as inverting image operation, brightness control, segmentation (threshold), and contrast stretching, is administered to seek out the most straightforward procedure to reinforce a biomedical image on FPGA. These techniques treated images of hand veins using the Open Access Biomedical Image program. It was clear from the studies that brightness controlling techniques enhance the image and provide better information. Developing an efficient architecture by the application of minimum blocks for digital signal processing (DSP) tool, which integrates itself with the high-level, yet easy to use the graphical interface of MATLAB Simulink environment and removes the necessity of the textual HDL programming is described in [4]. Hardware-level filters have been proposed for image processing (edge detection, sharpen operation, enhance contrast process, and brightness adjustment) to improve the quality of images and to support in diagnosis the medical specialist [6].

The DSP applications in medicine comprise signals of different dimensionalities and modalities, e.g., electroencephalogram (EEG), electrocardiogram (ECG), ultrasound, computerized axial tomography (CAT) scanners, magnetic resonance imaging (MRI), and holography among others as outlined in [7]. The analytic power, the problem-solving capabilities, and, therefore, the cost of the related systems are expanding continuously, as well as the dependence of recent medicine on them [7]. Thus, new types of filters are established at the hardware level for image processing (edge detection, sharpen operation, enhance contrast process, and brightness adjustment) to improve the quality of images and to support the medical diagnosis specialist [6, 8]. The results obtained with 512 × 512 images from [6] can be expanded to any size, as long as the FPGA memory has the necessary space to store the pictures. In [7], a new deblurring filter is proposed, which combines the Laplace filter and the Markov basis to boost the performance of colored images' processing. [9] offers a way to enhance real-time medical diagnosis using a dedicated computation engine to perform concentration index filtering, which is a kind of spatial filter optimized, aiming at full parallelism. To analyze the effect of applying a filtering technique on an image, [10] evaluates the filtering characteristics, by choosing a quality index. It speaks about how the application of special windows does image smoothening. [12] exploits concurrency at various levels in the implementation of the integration algorithm and general finite impulse response (FIR) filters to improve sampling/throughput rates.

13.3 Methodology

The process will first start by reshaping the given image to a binary sequence. Since any hardware device can only work on binary values, we can convert each layer (R-G-B) of the image into a binary sequence and feed it. The conversion of the image to a binary sequence can be easily done using Python, C++, or MATLAB. The implementation of various image processing techniques has been done using different filters. We have translated the kernel function to Verilog and implemented the convolution for a group of pixels surrounding a given pixel. The output after applying the filter is received back to reconstruct the image.

Each image pixel is represented by an 8-bit × 3 RGB values. The entire image is then converted to a sequence of pixels that can be accessed by its row and column values. The brightness, invert, and threshold operations work on individual pixels, whereas for sharpening and blurring operations, the pixel is passed through a 3 × 3 kernel, as shown in Fig. 13.1. The nine filter entries depend on the type of filter (kernel) and the operation. Figure 13.2 shows the banking operation that separates even and odd pixels. This method of parallelism enables faster functioning. However, we have compromised speed with the area, i.e., to achieve faster performance, we have utilized better hardware, thus occupying more space.

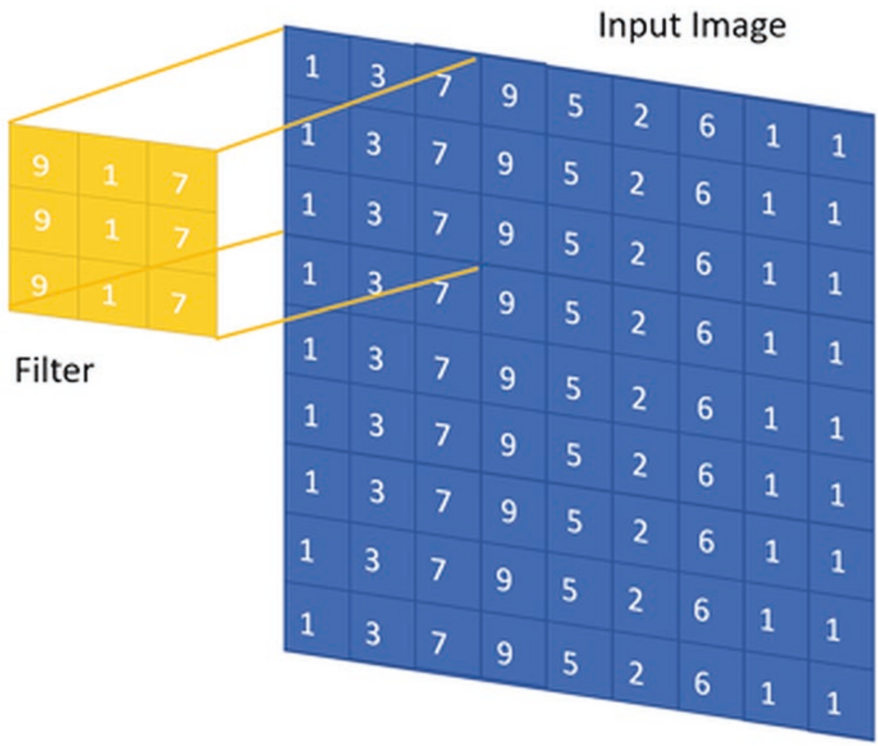


Fig. 13.1 Kernel application process

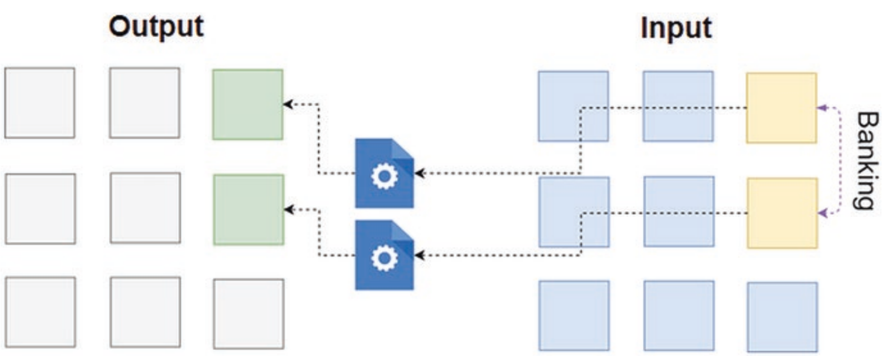


Fig. 13.2 Banking procedure used to improve performance

Image sharpening techniques are extensively employed to recover back the non-degraded image from its corrupted version and grant the image a sharper appearance because acquired images are considered as the degraded version of that view.

To blur an image, we use the blur filter, which looks like Fig. 13.3a. The rationale behind a filter like this is that blurring involves blending a pixel with its surrounding

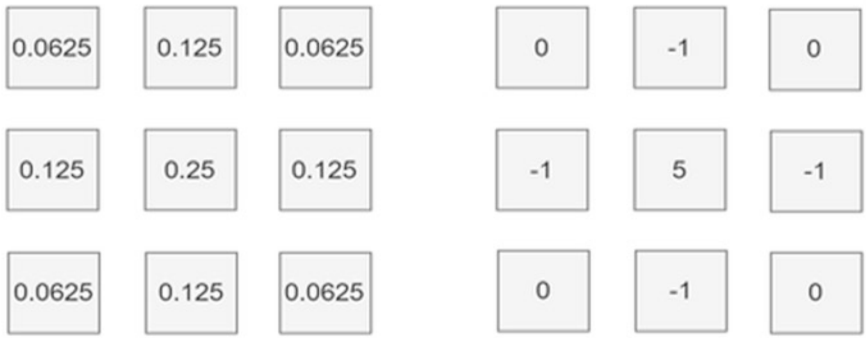


Fig. 13.3 (**a**) The blurring kernel and (**b**) sharpening kernel

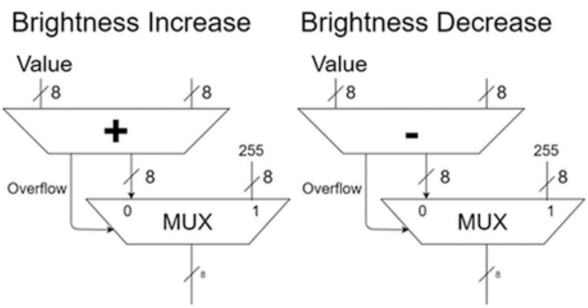


Fig. 13.4 Brightness increase and decrease hardware illustration

pixels. Thus, it takes a weighted mean such that the current pixel is focused more, but is blended slightly with the immediately neighboring pixels. Moreover, for sharpening, we use the filter shown in Fig. 13.3b.

Image sharpening techniques are extensively employed to recover back the undegraded image from its corrupted version and grant the image a sharper appearance because acquired images are considered as the degraded version of that view. Many reasons led to having blurry images, for instance, the finite size of the X-ray source focal spot, the detector element within the CT array, the imperfect resolution of the imaging system, and the data loss throughout image acquisition. The implementation of a brightness augmentation circuit requires a multiplexer (MUX) and an 8-bit adder circuit.

The brightness can be increased to any desired value provided the value of the pixel does not go above 255. As shown in Fig. 13.4, the implementation of a brightness decrease circuit requires a mux and an 8-bit subtractor circuit. The intensity can be decreased to any desired value provided the value of the pixel does not go below 0. Application in the medical field involves focusing on certain tissue by increasing its brightness while decreasing the light intensity of the surrounding tissue.

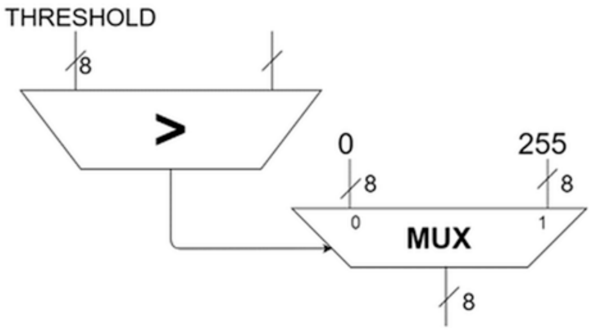


Fig. 13.5 Thresholding operation hardware illustration

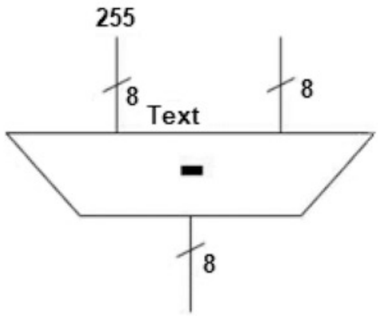


Fig. 13.6 Inversion operation hardware illustration

The threshold operation enhances an image by comparing the value of the pixel by a set threshold. Figure 13.5 shows this process. If the pixel value is greater than the threshold, the pixel is set to 255, else to 0. Here, 255 is white, and 0 is black.

Figure 13.6 illustrates the inversion operation implemented by a subtractor.

Certain tissues are usually surrounded by dark tissues, which makes it difficult to study them upon the inverting operation. The tissue we are interested in appears highlighted. The kernel is applied by multiplying each image pixel by its corresponding kernel pixel and supplied to an adder as described in Fig. 13.7. This adder acts as an accumulator that finally adds all the products and obtains the result for the pixel in question. Technically the kernel size can be modified to any size.

13.4 Experimental Results

A lung tissue sample image was taken and converted to a hexadecimal representation using MATLAB. It was then read into Verilog, and the image manipulation functions were applied. Figure 13.10 uses SEM alveoli in the lung [13] image to analyze the filters' output images outside the human lung [14]. A heart image is also analyzed [15].

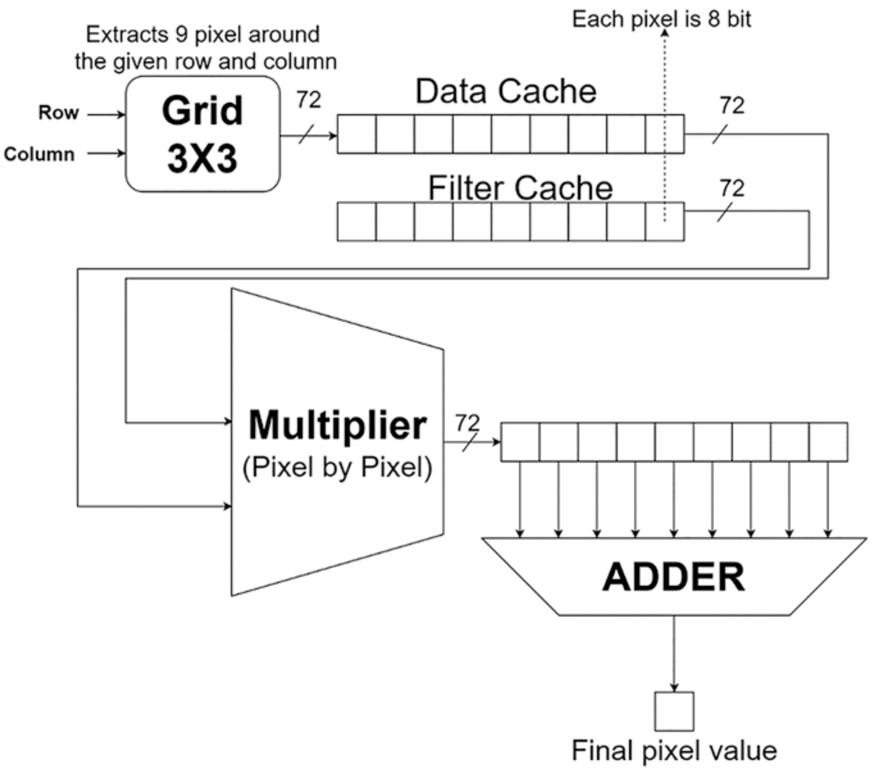


Fig. 13.7 Kernel application hardware illustration

The Verilog code yielded the image manipulation results seen in Figs. 13.8, 13.9, and 13.10 for brightness increase, inversion, threshold, blurring sharpening, grayscale, and outline operations. The outputs of the Verilog-based filters and those from the equivalent MATLAB implementations have been compared for the same sets of images. The FPGA-based solution is better to obtain the given type of image manipulation at a faster rate.

Figure 13.10 compares the MATLAB and Verilog outputs. We can observe that the outputs are similar. However, the Verilog code can be synthesized into an ASIC hardware or dumped on to FPGA, and therefore we can expect improvement in speed. Figures from 13.11 to 13.14 display results for blurring, sharpening, inverting, and threshold operations, respectively, against the original image. The red in the graph indicates filtered image pixel intensities, whereas the blue shows the original image pixel intensities. The pixel intensities are plotted here to analyze how an image has been modified after the application of the filter. This helps us to understand the image enhancement process better. For example, the waveform of the blurred image is seen to be smoother and has lesser spikes when compared to that of the original in Fig. 13.11. One can also observe that the blurred image from

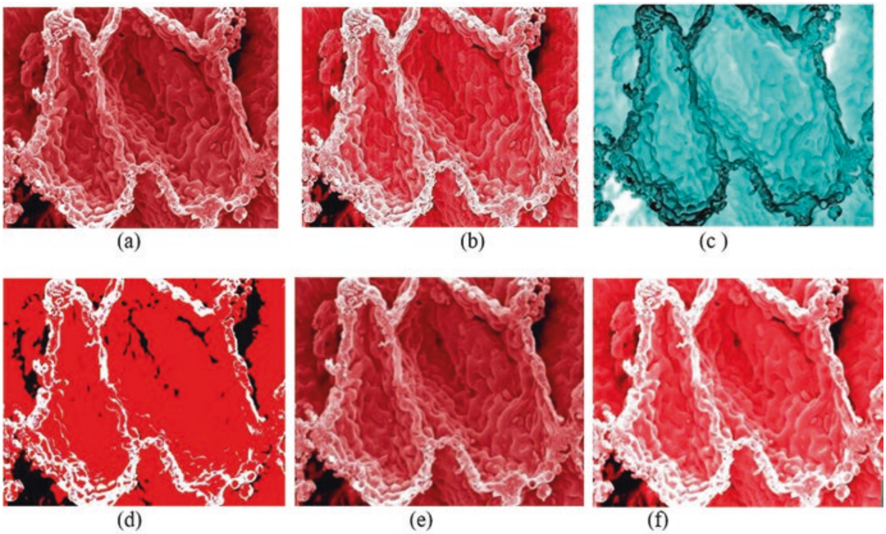


Fig. 13.8 Image of lung tissue: (**a**) original [11], (**b**) increased brightness, (**c**) inverted tissue, (**d**) threshold, (**e**) blur, and (**f**) sharping

Fig. 13.12 shows that the sharpened image has flatter regions of pixel intensities when compared to the original image. In Fig. 13.13, one can observe the pixel values have been swapped in the inverted image when compared to that of the original image. In Fig. 13.14 one can understand that threshold operation can be used to remove noise from when cleverly applied to certain portions of the picture.

13.5 Future Work

FPGAs accelerate computationally demanding tasks, particularly in image processing and computer vision, where their processing acceleration has become common. This happens even more often within an embedded environment, like medical equipment and drones [16–18], where the power consumption and computational resources of orthodox processors fail to handle the data throughput, intensive communication, cloud computing access, and computational requirements for real-time uses.

Short computational times are paramount for quick and trustworthy biomedical diagnostics, but these requirements increase the computational demand for new and better-quality imaging procedures. FPGAs are an alternative to multi-core architectures and graphic cards that can also support alternative hardware paradigms that adjust the hardware to the problem [19, 20].

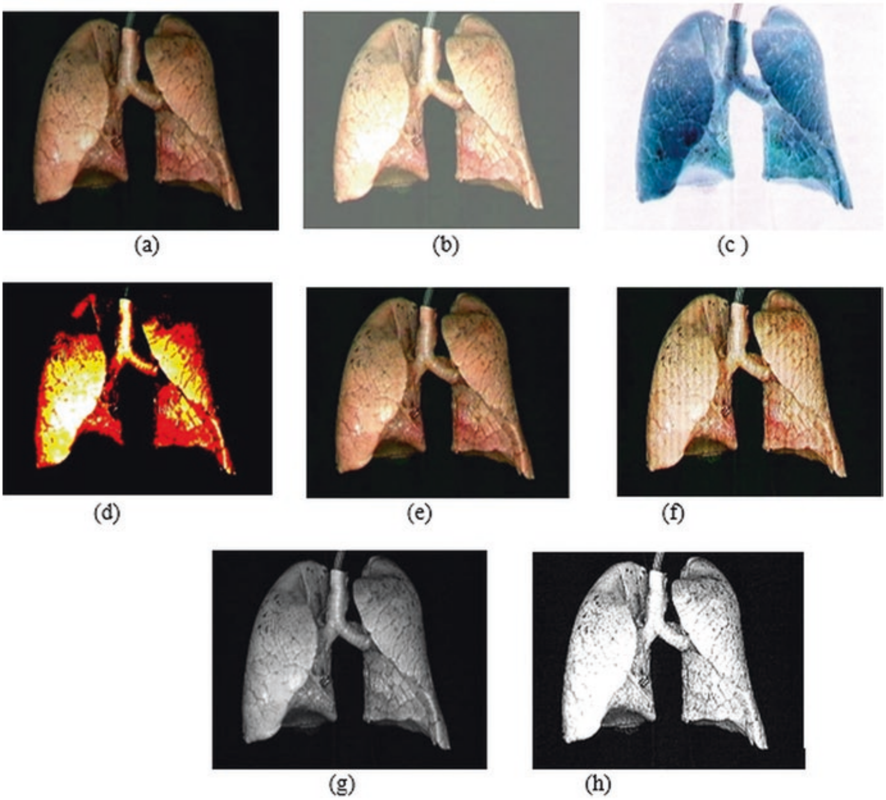


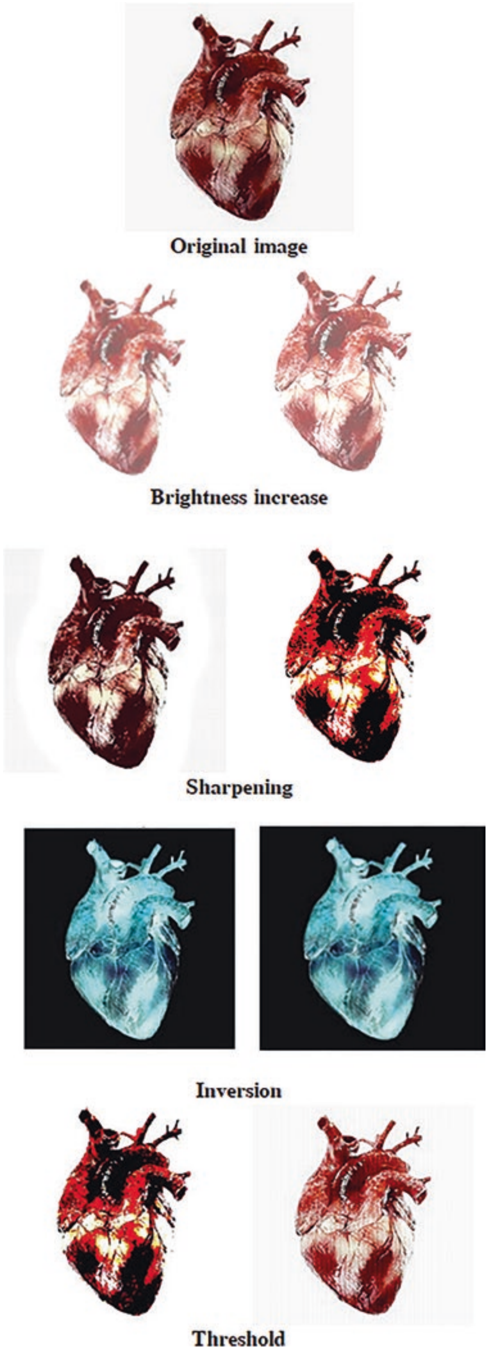
Fig. 13.9 Image of lungs: (**a**) original [11], (**b**) increased brightness, (**c**) inverted tissue, (**d**) threshold, (**e**) blur, (**f**) sharping, (**g**) grayscale, and (**h**) outline

In the upcoming years, embedded Network-on-Chip (NoC) will be much faster to expand the FPGA's existing arrangements of biosensors, bioactuators, blockchain-enabled devices, wires, switches, and other items to support large medical applications. Flexible interfaces between FPGAs structures, wireless networks, and embedded NoCs will permit several levels of modularity and scalability [21–23].

The authors would like to point out that multimodality imaging techniques involve data acquired by different kinds of sensors and different representations. ECG is one-dimensional, while other diagnostic equipment can work with 2D, 3D, and 4D images. High-dimensional images pose arduous computational load hardware- and software-wise [24–30].

The fast-developing hardware technologies relying on computational intelligence allow the deployment of the recommended design of this text on small and portable FPGA-based equipment and, consequently, easy incorporation or adaptation into existing portable systems [31, 32].

Fig. 13.10 Comparison of MATLAB (left) and Verilog (right) image outputs



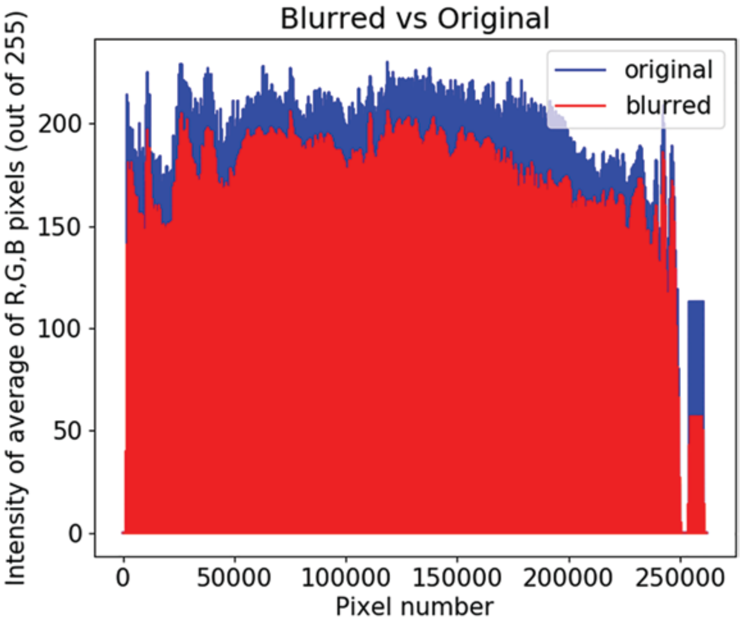


Fig. 13.11 Blurred vs original image pixel comparison

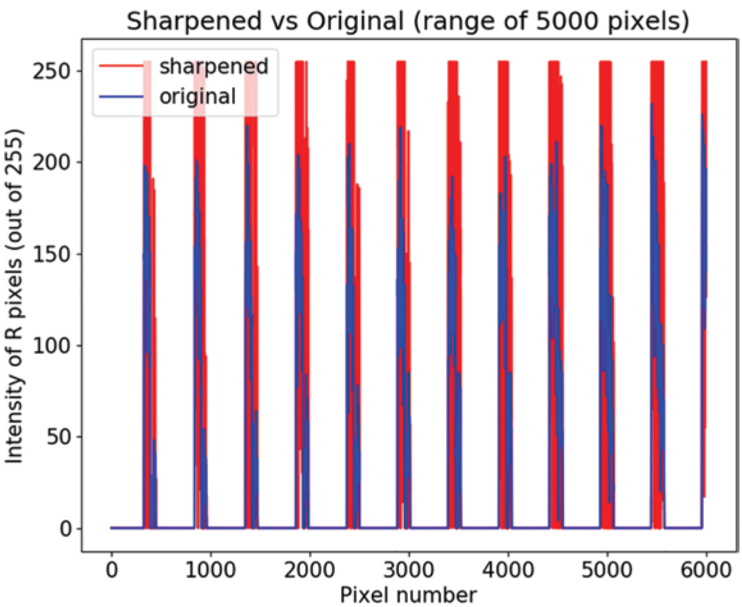


Fig. 13.12 Sharpened vs original images

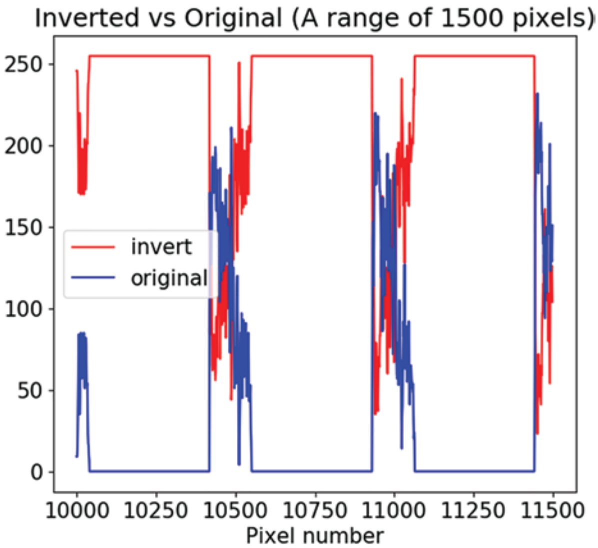


Fig. 13.13 Inverted vs original images

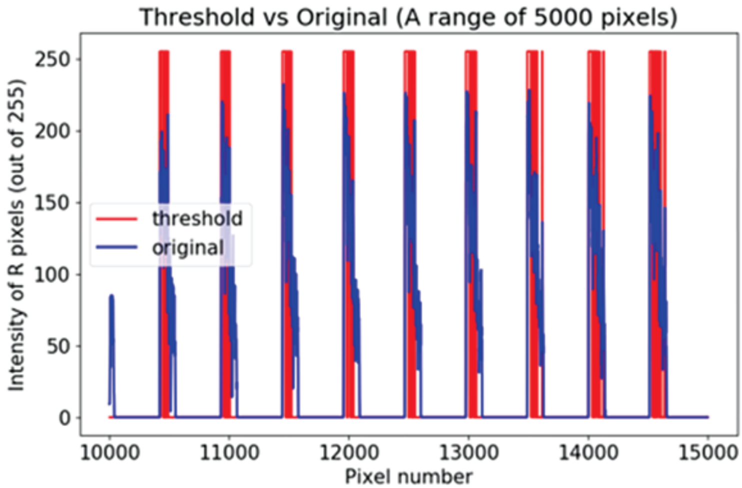


Fig. 13.14 Threshold vs original images

The authors are aware of the need to use objective metrics to evaluate the results, especially when working with different resolutions and zoom at the same time [33–37].

Optimization algorithms are frequently used in biomedical image processing, and they can handle mono-objective or multi-objective problems. Metaheuristic, aka nature-inspired algorithms, originates from the reflections about natural behaviors. Medical imaging can benefit from implementations of computational intelligence procedures in FPGAs to advance communication, database handling, image retrieval, etc. The phenomenal growth in the uses of FPGA technologies in healthcare occasioned several remarkable outcomes [38–43].

13.6 Conclusion

Embedded medical image processing designs built on FPGAs are ideal for delivering high performance with increasing picture resolutions and frame rates while permitting the addition of smart sensors/actuators, computer vision, and other novel technological innovations according to the cyber-physical system paradigm [44, 45].

FPGA improvement occurs due to the enormous speedup in the use and optimization given by hardware processing with excellent image quality. The FPGA realization leads to a better real-time performance in medical applications, where this can be used to improve the diagnosis speed and accuracy.

This work introduced a series of hardware-level filters for medical image processing to analyze the following operations: brightness adjustment, contrast enhancement, sharpening, blurring, grayscale, and outline. The present investigation relies on VLSI technologies because reconfigurable hardware devices provide higher speed than software implementations. The usage of a descriptive hardware language extends the field of circuitry to medical applications. Verilog Hardware Description Language (HDL) has opened the path toward the rapid hardware prototyping of further medical designs. Preliminary experimental outcomes for images of lungs and heart confirmed the benefit of employing softcore hardware.

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