Image Contrast Enhancement using Morphological Decomposition by Reconstruction

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Abstract: - The paper presents a novel algorithm for the computation of the image decomposition using a morphological filter with reconstruction The target applications are image contrast enhancement especially those with high dynamic content. Both bright and dark regions contrast enhancement were considered. A new hardware efficient implementation of decomposition is presented. Following decomposition in 5 levels of detail a local contrast enhancement is performed. The new reconstruction algorithm and its hardware implementation as proposed is shown to be independent on structural element size and that it results in a predictable time frame operation. A mixed schematic and VHDL/Verilog description of the decomposition filters was synthesized and results show far higher speed performance compared with solutions found in recent literature. The FPGA implementation had as main objective real time operation. The performance of the architecture was found to exceed real time conditions of operation and fit into medium size FPGA. A test sample image was used for contrast enhancement schemes validation. The white areas local contrast was enhanced expanding the gray scale for the detail levels after a parabolic series. The scale warping in the white areas resulted in contrast enhancement while the dark areas did not.

Key-Words: - image filtering, multi-dimensional kernel, FPGA implementation

1 Introduction

It is known that the major difficulty in using morphological filters in real time image processing applications is their inherent complexity and high computation cost.

In real time image processing applications the computational complexity issue is even more of a constraint. The solution advocated by recent literature is hardware acceleration by FPGA implementations of the algorithms [1] [2] [3].

High dynamic intensity images have poor contrast when perceived by the human vision. The final objective of the study was to devise hardware solutions for image contrast enhancement in real time for high dynamic content images. Both bright and dark regions contrast enhancement were considered as possible objectives.

Commonly the contrast is enhanced by local dilation of the intensity scale in the region of interest. The coefficients for scale dilation yield best results when adopted to human vision perception characteristics [5] The basics of contrast enhancement principles are presented in part 2 of the paper.

Morphological filters constitute a convenient and efficient method of contrast enhancement. Part 3 of the paper briefly reviews the principle of morphological filters for image decomposition according to the area parameter. The various computational alternatives are examined.

It is shown that the iterative mono dimensional structural element approach delivers lower performance given real time constraint when compared to multiple size structural element (SE).

A single scale multiple dimension structuring element (SE) variant was chosen as appropriate for FPGA implementation.

Part 4 of the paper presents a new computational approach for the reconstruction phase. As proposed it eliminates the computation time dependence on image content. The synthesis results show that the solution has an efficient implementation in medium size FPGA without need for external RAM .

In part 5 details of the proposed novel architecture implementation of the morphological image decomposition with reconstruction in FPGA.

Contrast enhancement on a sample image used for validation of the FPGA implementation as proposed is presented in part 6.

Part 7 of the paper contains a summary of the reported results and suggests further morphological algorithm enhancements .

2 Morphological Image Contrast Enhancement

The information content in an image is known to be very high. The image representation for perception of the information content is dependent on the observer capacity to distinguish among the salient objects of interest.

A contrast enhancement method is a way to construct starting from the original image an appropriate representation highlighting to the observer for perception the image objects with features of interest.

In general terms this means to alter the scale of details in the representation favoring the desired features. In the case of contrast enhancement from the original image feature space some details at local scale are expanded to be brought into focus. They will attract the attention of the observer while the rest are contracted to recede in perception.

The most common method of contrast enhancement in use today is the histogram equalization [6]. The draw back of histogram equalization is that the results obtained in th end are input image dependent.

The dynamic range of images is known to be very large. In a representation at a limited resolution even if generous in resources compromises as to which aspects of interest value range to be allocated from the ones available. The details are the features that do pose a lot of interest. The interest is in contrast with their natural minor representation in the gray levels being overshadowed by large area objects.

Natural images do have a Fourier spectrum that is of the $1/f^{-\mathbf{a}}$ form with $\boldsymbol{a}$ in a range (0.7 – 1.5). As the spacial frequency $\boldsymbol{f}$ increases the amplitude of the details decreases thus making them always more difficult to represent.

Specific application areas do present images that span selectively on ranges of the general image spectrum. Compact object populated scenes claim the extremes of the spectrum while inner images of compact structures exhibit center spatial frequencies spectral domain. A different contrast enhancement scheme must be devised for each class.

The human vision system perceives images in a complex and non linear fashion. It is therefore natural to follow the human system perception rules in order to be able to highlight the features of interest.

The system architecture outlined in Fig. 1 indicates the method of image details scale change having as final objective the human contrast perception enhancement.

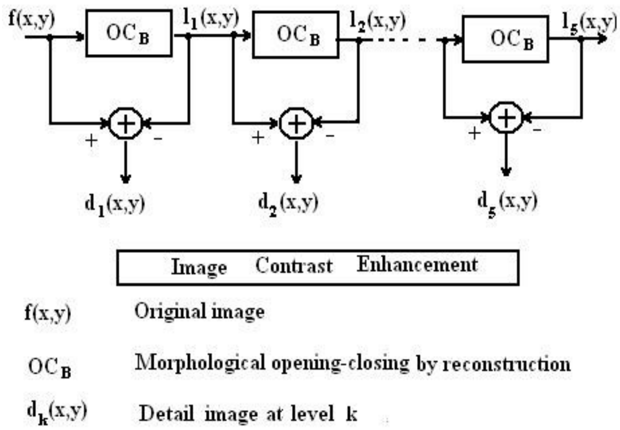

Fig. 1 Image contrast enhancement principle using morphological image decomposition.

The solution adopted in the present paper is to decompose the original image information in the scale space of the human vision system to start with. The second step adjusts the image levels at every scale of details into a representation favoring the perception of features of interest by the human eye.

Classical contrast enhancement schemes use global rearrangement of image intensity levels to balance image representation for perception [7], [8].

The advantage of the morphological decomposition and representation over normal pixel intensity representation is that it relates to features rather than just intensity numerical values [14].

Morphological operators used in the image decomposition extract from intensity content the variational content populating the original larger dimension space with objects. The pixel intensities are not taken as singular values but as a map of objects of the real space projected on the 2D image.

The image decomposed in detail levels is processed and subsequently assembled back. Features in image can thus be enhanced or deemed with ought affecting the rest of the objects in the image.

3 Morphological image decomposition

Image enhancement using morphological methods are of considerable contemporary interest as reflected in recent literature [4], [12], [15]. It is also well known that for each application class specific enhancement methods need to be developed.

The decomposition of a image in levels of detail is equivalent to low pass filtering as it is illustrated in Fig. 2.

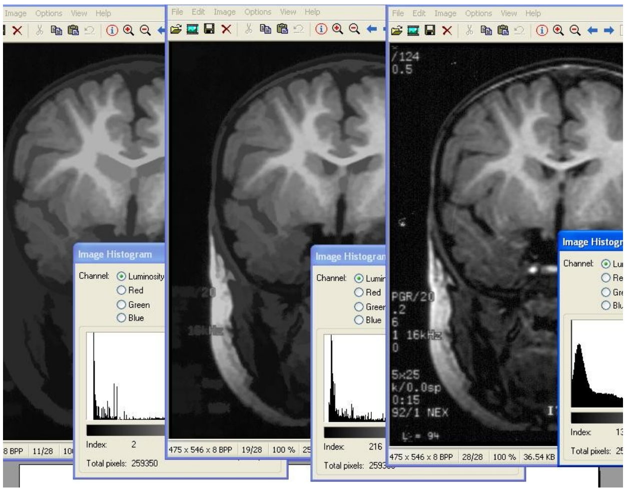

Fig. 2 Low pass filtering with reconstruction visible mostly in the dark areas for a test sample using 5x5 and 9x9 SE. The image at the right is the original.

The sequence of successive opening and closing with structuring elements of increasing size selects the levels of detail hence the spatial frequencies.

The image decomposition and scale rearrangement principles is well understood as reflected in the literature. Efficient technological implementations for classes of applications that can not afford a high computational resource have not been explored [4].

The difficulty of hardware implementation of image processing algorithms is due to the very high complexity of the algorithm and the high amount of computation necessary [9], [10].

In the present paper the implementation of morphological filters is mirroring the decomposition of the image as proposed recently, following the human vision system (HVS) perception process [5].

The image multi-resolution representation proposed in the present work is based on a morphological single scale decomposition. The classes of objects are selected at each level using a closure – opening (CO) morphological operator pair. It can be shown that this succession of operators is acting equivalent to a low pass filter at the level of details of objects in the image. The selective detail sub-image is obtained by subtracting of the filtered image from the original.

The definition for the dilation and erosion operators for a grayscale image using a structuring element *[SE]* - **B** (j,k) is as follows:

$$\mathbf{Dil(A(r,s),B) = maxB_{(j,k)}\,(A(r\text{-}j,s\text{-}k) + B\,(j,k))} \quad (1)$$

$$\mathbf{Ero(A(r,s),B) = minB_{(j,k)}\,(A(r\text{-}j,s\text{-}k) - B\,(j,k))} \quad (2)$$

A succession of dilation and erosion operations define the morphological closing and opening operators :

$$\mathbf{Close(Image,B) = Ero(Dil(Image,B),B)} \quad (3)$$

$$\mathbf{Open(Image, B) = Dil(Ero(Image,B), B)} \quad (4)$$

To obtain a morphological low pass filter with ought image distortion each of the closing and opening operators must be followed by an appropriate reconstruction. The geodesic dilation and the geodesic erosion of size one are given by:

$$\mathbf{G_1Dil[I\ (mark)F] = min[I, Dil_1(F)]} \quad \text{with } \mathbf{F \le I} \ (5)$$

$$\mathbf{G_1Ero[I\ (mark)F] = max[I, Ero_1(F)]} \quad \text{with } \mathbf{F \ge I} \ (6)$$

The original image **I** is reconstructed based on the mark image **F** that needs to full fill the ordering condition given in formula (5) and (6).

An illustration of how levels of detail are obtained in morphological image decomposition is presented in Fig. 3. for a 2D case. The 3D case is similar by adding another dimension. The reconstruction fills back the distorted intensity surfaces values by the planar sides of the structuring element.

The structuring element (SE) at one level is the dilation of the previous level with itself.

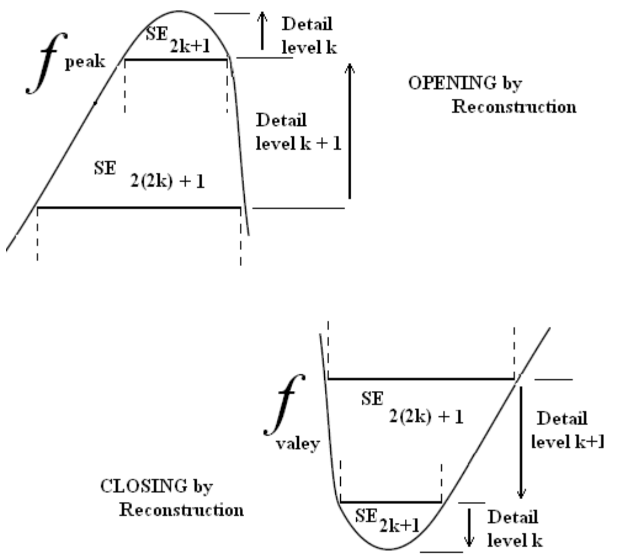

Fig 3 Successive detachment of detail layers from image in the decomposition by reconstruction using multiple dimension SE.

The structuring element dimension SE is doubled at each stage and trimmed by one to be an odd number.

When filters by reconstruction are used, as basic geodesic transformations, the geodesic dilation and the geodesic erosion of size one, are iterated until idempotence is reached:

RDil[I (mark)F] = {G_1Dil & G_1Dil& … G_1Dil} (7)

REro[I(mark)F]={G_1Ero&G_1Ero&…G_1ERO} (8)

The iteration runs for a arbitrary number **m** as necessary depending on image **I** and mark **F.**

The number of iterations is variable and dependent on image content. This characteristic will lead to an unpredictable timing performance with large costs when implemented in hardware.

According to the original work the matrix of the structuring element (SE) must span the range of dimension from 3 to 33 with the following values {3,5,9,17,33} [5].

Five levels of detail have been shown to be sufficient for contrast enhancement. For the larger objects in the image corresponding to SE of dimension larger then 33 it has been proven there is no need for contrast enhancement. They cover more than 1 % in the user field of view and are subject to eye adaptive perception.

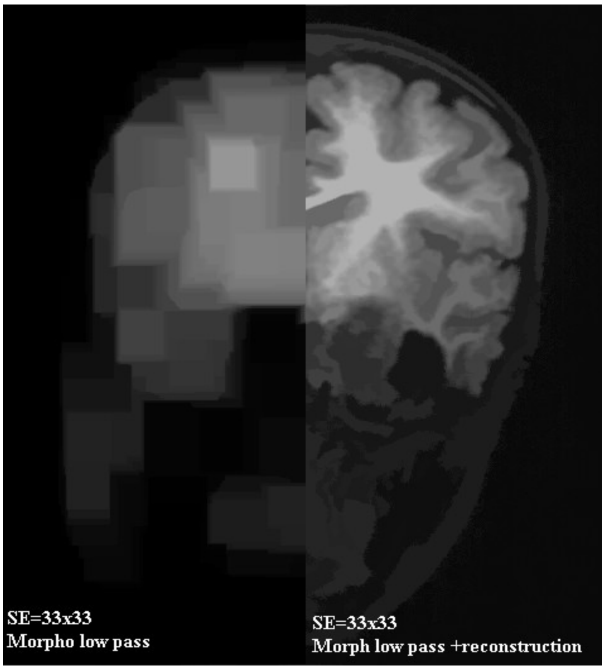

Fig. 4 MathLab simulation of morphological image decomposition with reconstruction .

The output after the fifth filter level is an image with a yet considerable amount of information named - *no detail image*.

In order to test the new architecture as proposed a MathLab simulation of the filtering action on a test image was conducted.

We followed the original work selecting the spatial frequencies at each level of detail are determined as optimal for the HVS perception [5]. The level separation parameter values have been determined following a contrast perception study.

An alternative to using a single scale and multiple dimensions SE is the use a single dimension structural element. The filtering of levels of detail can be obtained by multiple successive applications of elementary erosions and dilations. Such an architecture is attractive for hardware implementation since it promises silicon area cost effective implementations.

The disadvantage of this type of architecture is that the frame processing period increases proportional to the number of operations in the morphological processing chain.

The storage of intermediary images in waiting for successive elementary filtering raises constrains on memory resources necessary. Since storage is the major resource bottleneck such a solution loses its simplicity advantage. In the end the real draw back of this architecture is the exponential increase in the computation time.

4 Morphological image decomposition for hardware implementation

In applications of image contrast enhancement in real time the computational complexity and frame rates are the two constrains that both need to be satisfied.

The solution selected for the implemented and found most appropriate to perform a efficient decomposition of the image was a pyramid of content of details.

The optimization of morphological operations when implemented in hardware has different conditioning parameters then when done computationally [11], [12].

The capacity of the recent available computational hardware can sustain parallel implementation when necessary thus offering a huge advantage over one computational node classical machines.

Three criteria have been identified that differentiate computational implementations of algorithms compared with FPGA implementations.

Criterion I.
The number of *processing units* available normally is one or a few in the case of a vector engine. In FPGA the number of processing units can be made virtually as large as the number of pixels in the image.

Criterion II.
The second major difference is related to *memory availability*. Although in present FPGA there are RAM memory banks, an algorithm implementation is not constructed by storing values in RAM. The FPGA logic gate fabric run length (incorporating distributed RAM) actually implements the processing imposed by the algorithm.

Criterion III.
The image processing with FPGA hardware acceleration is mainly aiming real time applications. The natural line by line raster exploration of the image must be accommodated.

The algorithm must therefore be implementation in the pipeline mode. Storage is used for operand ordering only.

Staring from the above observations the following general strategic methods are to be used for algorithm speed up under hardware implementation:

a) The speed of the processing is not dependent on the amount of computations done per image pixels as is the case with classical computational algorithm speed up criterion.

b) When using a FPGA implementation the speed of the processing is dependent on the length of the pipeline since this determines the time delay for the next processing operator on the image.

In the case of the morphological filtering the blind time period can extend to as much as a fraction of the image frame period. For example for 256x256 pixels image and a SE of maximum size 33x33 the pipe time restriction extends to 15% of the frame period.

The conclusion from the above arguments resulted in a clear direction of implementation:

I. Full SE dimension used directly results in better real time performance as opposed with unitary (or small) SE used recursively.

II. The reconstruction part of the morphological filtering following its definition is inherently recursive (see formulas (7) and (8)). The novel algorithm according to formulas (9) and (10) is image content independent.

For large SE the classical unit SE algorithm can extend in time quite prohibitively. Recent solutions have been proposed to cope with the problem [15] [16]. Both above mentioned methods are very heavily dependent on the intermediary storage – implemented in queues.

In the present paper we propose and prove the efficiency of a computation method that is not only well suited for FPGA implementation but is accelerating even in the case of computational implementation in software.

Starting from definition formula (7) and (8) we propose the following factoring leading to a very efficient hardware implementation.

Starting with an opening using a SE of size ***2n+1*** it is easy to see that the reconstruction iterations are bound by a finite number **m** very often less then the size of the SE.

Our novel algorithm and its FPGA implementation is outlined in Fig. 5 and is similar to a the pyramidal method described previously in literature indicating very large computational savings [13], [10].

A1. Proposition:
Dilation and erosion by reconstruction defined by formula (7), (8) are equivalent to formula (9),(10).

The proposition A1 needs to be interpreted in the sense that although mathematically equivalent the form in (9) and (10) is far more efficient to implement in hardware.

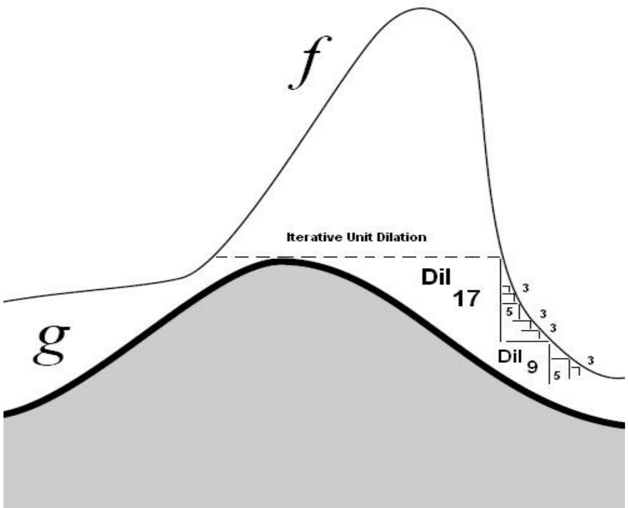

Fig. 5 Single scale multiple dimension SE opening by reconstruction new computation principle.

For a operation with a structuring element SE of ***2n+1*** pixels the reconstruction series starts with a SE of dimension ***n***. The most advantageous for hardware implementation is the binary series of SE dimension. This makes the reconstruction module share the same architecture with the basic morphological operations.

RDil[I (mark)F] = {G_nDil & G_{n-1}Dil& ...G_1Dil} (9)

REro[I(mark)F]={G_nEro&G_{n-1}Ero&..G_1Ero}(10)

The aggregation of unitary operations in higher order dilations/erosions is using the well known *linear decomposition* property of the erosion and dilation operators with flat SE in reverse order.

A number of interesting corollaries can be deduced from the above property. In this paper we present the most important hardware implementation effect. The equivalent form opens up the possibility of using the same hardware implementation for the SE as in erosion and dilation operations.

Computationally the form of the equation has little consequences if at all. Each mathematical representation form when implemented in hardware suggests a very different implementation. The iterated unit operations will end up in a simple circuit evolving in time. The higher order SE operations on the other hand are best implemented in hardware in a parallel multiple computational structure.

5 FPGA implementation of morphological filters

The problems inherent to most filter algorithm that needed examination are the margin effect and the repeated pixel value processing for SE windows at just one step distance [10].

In Fig. 6. a data flow model is presented for the FPGA-based implementation of the image decomposition using morphological operators.

The operations for one level of detail filter is a succession with a predefined order. The SE operating blocks can be cascaded on the same image lines pixel values if appropriate timing delays are observed.

The general requirement for the time delay in between two successive morphological operator blocks is given by the following formula:

Delay = [d(SEn-1) + d(SEm-1)]/2 + 1 (11)

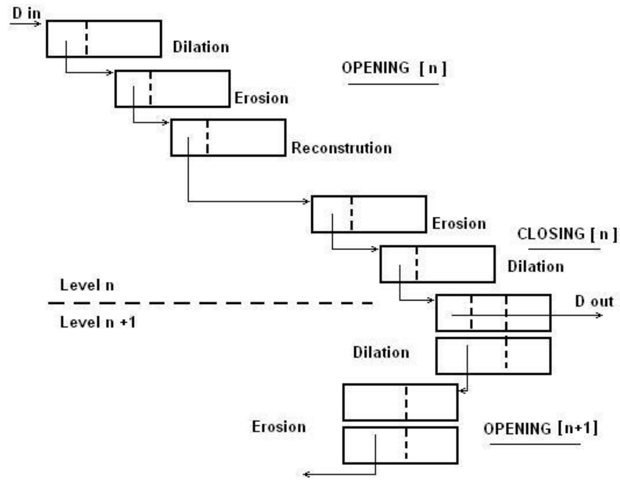

Fig. 6 Sketch of data flow in the decomposition with reconstruction algorithm hardware architecture.

The problem of the margin effect has a simple solution for gray level min/max calculations. The missing parts of the window are initialized at either max respectively min of the range and thus will not influence the result and suppress edge effect.

The successive SE processing blocks and associated FIFO feed into one another. It is thus observed that the sequential nature of the algorithm imposes storage of the intermediate results before proceeding with the next dimension SE processing.

The proposed architecture limits the amount of superposition of the successive SE partial results to part of the the dimension of the next SE.

From a timing point of view as soon as the following SE has accumulated sufficient lines to start processing no further buffering is necessary. The current layer output level detail data can be shifted out for next block processing for direct storage.

The dimension parameter of the SE (denoted **n)** according to the HVS contrast enhancement scheme spans only the range of{1, 2, 4, 8 and 16}. Higher values are not useful to human perception.

The implementation of the algorithm for one line of the raster image of length **k** is outlined in Fig. 7. Only one line of the image is presented since the rest are similar in architecture.

The SE covers at one time a number of image lines equal to its dimension. The first part of the line covered by the SE is stored in a raw of registers while the rest of the line is stored in long shift register or FIFO stack. The FIFO is best implemented in the BRAM resource of the FPGA thus saving resources.

To simplify the SE min/max ordering circuitry an orthogonal decomposition of the computation on the two dimensions of the SE is used. The advancing line of SE pixel values min/max is obtained by a comparator running horizontally. Local SE columns min/max values thus determined are stored in a stack (line) with latest useful values determined.

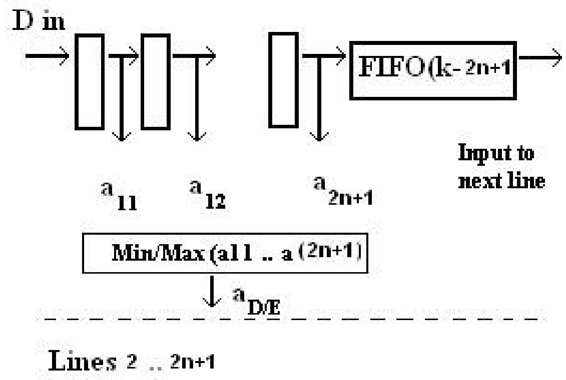

Fig. 7. Block diagram of the FPGA implementation of image line morphological decomposition.

The evaluation of the min/max value received the design found as the most appropriate for the architecture proposed. It is based on a sequential pixel value comparison per columns and storage of the rest of previous lines maximum for the SE.

The functioning of the morphological low pass filter algorithm implemented in a circuit is composed of the following phases:

1. Line min/max

The comparators are cascaded in a pyramid structure of compare and store the min/max result in an 8 bit accumulator. An outline of the schematic for the line processor is given in Fig. 8.

2. SE last lines min/max

For each SE line latest maximum values are stored in stack of an **2n+1** registers with their own set of comparator in a second phase of the process. The min/max of the values of the whole SE is a circuit identical to the line comparator that sorts the last lines local min/max values determined in the line min/max phase.

3. Shift phase

The data in storage and SE line values are shifted one step to accommodate a next complete cycle of computation. The last line maximum is deleted and space in created in the FIFO for the new line.

The calculation of the min/max for one pixel was implemented with a manually optimized schematic based design presented in Fig. 8. The circuit is an asynchronous comparator circuit requiring just eight slices of FPGA CLB per pixel.

The implementation is of pipeline type with a pipe length of k+1 for a column hight of 2k+1.

The pyramid of comparators uses a 'compare and transfer' the min/max values to the next level of higher order having a divided by two number of values. The SE dimensions are odd and therefore one pixel value will be left outside the scheme until the last stage. To preserve the pipeline property of the circuit the extra value is shifted by a set of registers until it is operated upon in the last comparison.

The time delay of k+1 shift periods must be observed in the succession of the following morphological operation in the set.

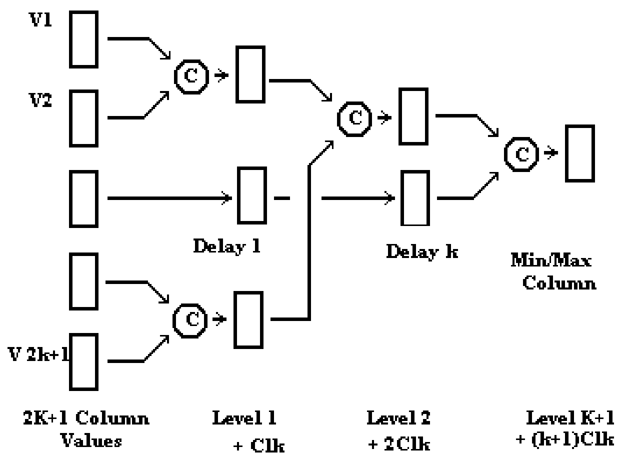

Fig. 8 The circuit schematics of the synchronous k+1 stage pipelined comparator.

It is important to note that the reconstruction operation is implemented using the same architecture as for the min/max (opening and closing) operations making synchronism possible.

During the image reconstruction the delays accumulated in the decomposition stages must be compensated by equal delays in opposite order in order to synchronize the detail contrast enhanced images before processed image assembly.

The pipeline has a hardware implementation cost that only doubles the number of registers used for column value storage.

Table 1 is a summary of sample results of several variant VHDL and manual component instantiations used to test design performance.

The FIFO was synthesized using the OpenCores VHDL GenericFIFO code, and the Min/Max local store and comparator circuit instantiated as manually optimized schematic components.

The sample cases presented use Xilinx and Altera devices as target FPGA for a morphological filter decomposing a image 512x512 with 8 bit /pixel.

Table 1

Target FPGA	**Reso-lution**	**Slices/ Cells**	**RAM Use**	**Start Latency**
Xilinx-Virtex XCV1000E	512x512	74%	80%	1.5
Altera -Cyclone EP2C35	256x256	40%	45%	2.0

As it can be seen from the sample synthesis results the design fits within a medium size FPGA. The pipeline has a latency of the order of a few pixel periods, delay that can easily compensated with a delay stack to synchronize frames for later processing.

The timing of the operator blocks has a considerable complexity to be detailed in this paper. The operation delays counts in pixel image shifts and the solution used for all was pixel delay stacks.

6 White areas morphological contrast enhancement

Progressive detail level based contrast enhancement has notable results as reported in the literature but it is known to have room for improvement [16][17].

The adaptivity property of the human visual system is one part of the system that must be accounted for. The human eye is more sensitive to finer details than to larger areas with different intensity.

Ends of scale close to minimum intensity (black) as well as maximum intensity details (white) transformations that depart from linearity can be the object of contrast enhancement.

The large and middle size details observed by a human visual system with adaptation need no changes aside from range restrictions. Fig.8 presents the gray level reservation scheme for a white areas contrast enhancement case. A similar arrangement can be made for the dark regions in the image.

The detail levels amplitudes are scaled up according to a progressive scale. The coefficients for optimal human eye perception are known from experimental data. The general form is a power function with the exponent in the range [0.5 to 1.5].

In order to accommodate this perception scale the detail levels need to be multiplied by emphasis coefficients forming a power series with a similar form.

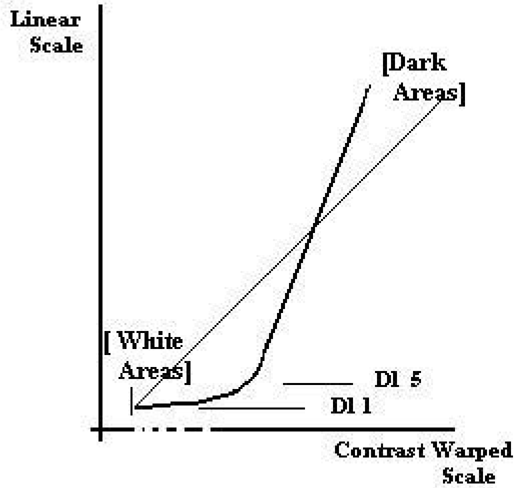

Fig. 9 Intensity scale warping for small details in dark areas of the intensity scale.

The image intensity value range is fixed (256 levels of gray) and accommodation of contrast enhanced extended ranges must be at the expense of the rest of the image areas gray scale ranges. The ranges not exposed to contrast enhancement are compressed to make room for the enhanced ranges.

In practical situations the contrast enhancement schemes are dependent on the image characteristics. Some areas may support enhancements while others do not.

All level intensity perception is linked to the next level because they appear in the image as background for the former. The contrast sensitivity dependence of the human visual system at on level of detail its on background intensity is well known.

Ideally the contrast adjustment process must start with the lowest detail image – no detail image as background. Being a image level with large flat areas from where the details have been removed no contrast enhancement is required. Contrast adjustment at this level may be needed though in applications with very high dynamic range images.

The following smaller detail image contrast and enhancement coefficient will be determined with respect to its background image level.

For all subsequent detail layers all previous layers as adjusted and added to the previous layer will form the level background reference. The contrast enhancement coefficient for the current layer are than calculated based on all previous levels.

In order to validate the method exposed a test image white areas was contrast enhanced using the level scaling coefficients from Table 2. The binary values where used as an approximation of experimental coefficients for reasons of simpler hardware implementation.

Other similar approximations to the experimental data have been used. The results obtained did not exhibit noticeable differences. This result validates our approach of using a scale set of factors in powers of 2 for ease of digital implementation.

Table 2

New Scale	**[Dl 1]**	**Dl 2**	**Dl 3**	**Dl 4**	**Dl 5**
Binary Power warping	[2]	4	8	4	2
Experimental coefficients	1	3.1	9.4	5.2	3

The results of the image white areas contrast enhancement are presented in Fig. 10. The 'no detail' image was compressed by a ½ coefficient applied to all values.

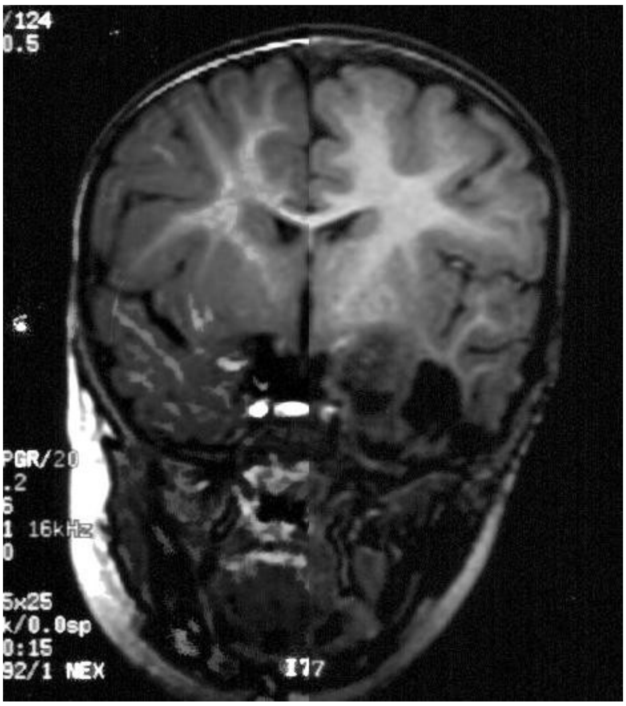

Fig. 10 Contrast enhancement of the white areas (left half) and original image (right half).

A second attempt to use the same procedure for the black areas failed. The test image black (lower) areas are not suitable for contrast enhancement being very 'flat' with most regions at the same gray level.

The smallest detail level was suppressed in contrast enhancement because it contains noise in large proportion and its amplification must be limited. The image details contained in the first level image can be added to the image after a noise removing procedure.

The performance of the contrast enhancement was assessed visually. A more complex measure method should be devised including both equipment and real human subjects perception.

The results of image decomposition and contrast enhancement are known to be dependent on the image and as such a selected set of test images specific for contrast enhancement is necessary.

Further work is necessary in the catenation of the contrast enhanced regions and the rest of the image. The gray scale gradients matching may improve the integration of the enhanced areas in the final image.

7 Conclusions

The results of the implementation in FPGA of a morphological multiple dimensional kernel filter are presented. The study was centered on image contrast enhancement for visualization.

The focus of the study was the optimization of the silicon area and sample frame throughput to meat the real time constraint of the image viewing.

The application of the novel equivalent reconstruction algorithm was found to be very computationally efficient. The estimations show improvements in speed of orders of magnitude over previous methods used.

Synthesis results of a mixed schematic and VHDL description of the decomposition filters indicate a low enough resource count to fit in a FPGA. The performance of the architecture is proven to exceed real time conditions of operation.

The details of the FPGA implementation support the performance with a architecture that requires a minimum of resources. The architecture proposed if fully pipelined. The timing constraints due to the delays necessary in between operations are independent of image content.

Contrast enhancement on a sample images for white areas was used to validated the method. The performance of the contrast enhancement was not among the objectives of the present work and needs further investigations.

The results obtained so far are encouraging as far as decomposition performance is concerned. The calculation of a new contrast for each detailed image and assembly of the enhanced image remains as tasks for future work. .

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