Parallel image and video processing on distributed computer systems

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Abstract. The aim of the paper is to validate architectures that allow an image processing researcher to develop parallel applications. A comparative analysis of the possible software and hardware solutions for real-time image and video processing was presented, with emphasis on distributed computing. The challenge was to develop algorithms that perform real-time low level operations on digital images able to be executed on a cluster of desktop PCs. The experiments on a case study show how to use parallelizable patterns and how to optimize the load balancing between the workstations.
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Keywords: real-time image processing, low level operations, parallel and distributed processing, tasks scheduling, lines detection, directional filtering.

1 Introduction

Considering the need for real-time image processing and how this need can be met by exploiting the inherent parallelism in an algorithm, it becomes important to discuss what exactly is meant by the term "real-time," an elusive term that is often used to describe a wide variety of image processing systems and algorithms. From the literature, it can be derived that there are three main interpretations of the concept of "real-time", namely real-time in the perceptual sense, real-time in the software engineering sense, and real-time in the signal processing sense.

Real-time in the perceptual sense is used mainly to describe the interaction between a human and a computer device for a near instantaneous response of the device to an input by a human user. For instance, Bovik defines the concept of "real-time" in the context of video processing, describing that "*the result of processing appears effectively* '*instantaneously*' *(usually in a perceptual sense) once the input becomes available*"[1]. Note that "real-time" imposes a maximum tolerable delay based on human perception of delay, which is essentially some sort of application-dependent bounded response time.

Real-time in the software engineering sense is also based on the concept of a bounded response time as in the perceptual sense. Dougherty and Laplante [2] point out that a "*real-time system is one that must satisfy explicit bounded response time constraints to avoid failure*". So, soft real-time refers to the case where missed real-time deadlines result in performance degradation rather than failure.

Real-time in the signal processing sense is based on the idea of completing processing in the time available between successive input samples [3]. An important item of note here is that one way to gauge the "real-time" status of an algorithm is to determine some measure of the amount of time it takes for the algorithm to complete all requisite transferring and processing of image data, and then making sure that it is less than the allotted time for processing.

2 Software operations involved in real time image processing

2.1 Levels of image processing operations

The digital primary processing mainly consists of three stages: noise rejection, binary representation, and edge extraction. Due to the fact that the noise can introduce errors in other stages (like contour detection and feature extraction), the image noise rejection must be the first stage in any digital image processing application. For these algorithms it is recommend local operators which act in symmetrical neighborhoods of the considered pixels. They have the advantage of simplicity and they can be implemented easily implemented on dedicated hardware structures. This approach changes when considering software processing. Digital images are essentially multidimensional signals and are thus quite data intensive, requiring a significant amount of computation and memory resources for their processing. The key to cope with this issue is the concept of parallel processing who deals with computations on large data sets. In fact, much of what goes into implementing an efficient image/video processing system centers on how well the implementation, both hardware and software, exploits different forms of parallelism in an algorithm, which can be data level parallelism - DLP or/and instruction level parallelism – ILP [4]. DLP manifests itself in the application of the same operation on different sets of data, while ILP manifests itself in scheduling the simultaneous execution of multiple independent operations in a pipeline fashion.

Traditionally, image processing operations have been classified into three main levels, namely low, intermediate, and high, where each successive level differs in its input/output data relationship [5]. Low-level operators take an image as their input and produce an image as their output, while intermediate-level operators take an image as their input and generate image attributes as their output, and finally high-level operators take image attributes as their inputs and interpret the attributes, usually producing some kind of knowledge-based control at their output.

One can hope that with an adequate task scheduling and a well designed cluster of processors one can perform in real time low-level operations by software parallelization.

Low-level operations transform image data to image data. This means that such operators deal directly with image matrix data at the pixel level. Examples of such operations include color transformations, gamma correction, linear or nonlinear filtering, noise reduction, sharpness enhancement, frequency domain transformations, etc. The ultimate goal of such operations is to either enhance image data, possibly to emphasize certain key features, preparing them for viewing by humans, or extract features for processing at the intermediate-level. These operations can be further classified into point, neighborhood (local), and global operations [6]. Point operations are the simplest of the low-level operations since a given input pixel is transformed into an output pixel, where the transformation does not depend on any of the pixels surrounding the input pixel. Such operations include arithmetic operations, logical operations, table lookups, threshold operations, etc. The inherent DLP in such operations is obvious, as depicted in Fig. 1 (a), where the point operation on the pixel shown in black needs to be performed across all the pixels in the input image. Local neighborhood operations are more complex than point operations in that the transformation from an input pixel to an output pixel depends on a neighborhood of the input pixel. Such operations include two-dimensional spatial convolution and filtering, smoothing, sharpening, image enhancement, etc. Since each output pixel is some function of the input pixel and its neighbors, these operations require a large amount of computations. The inherent parallelism in such operations is illustrated in Fig. 1 (b), where the local neighborhood operation on the pixel shown in black needs to be performed across all the pixels in the input image. Finally, global operations build upon neighborhood operations in which a single output pixel depends on every pixel in the input image (see Fig. 1 (c)).

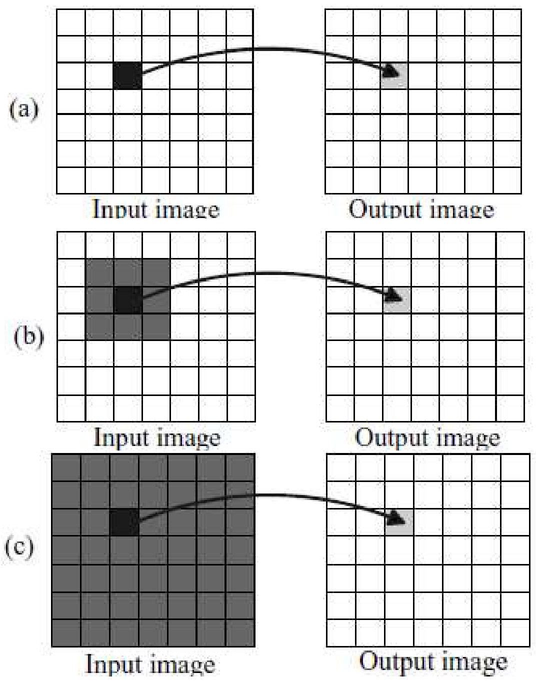

Fig.1.Parallelism in low-level image processing: a) point b) neighborhood c) global

All low-level operations involve nested looping through all the pixels in an input image with the innermost loop applying a point, neighborhood, or global operator to obtain the pixels forming an output image. For this reason low-level operations are excellent candidates for exploiting DLP.

The higher degree operations are difficult to implement for real time execution. Intermediate-level operations transform image data to a slightly more abstract form of information by extracting certain attributes or features of interest from an image. This means that such operations also deal with the image at the pixel level, but a key difference is that the transformations involved cause a reduction in the amount of data from input to output. The goal by carrying out these operations (which include segmenting an image into regions/objects of interest, extracting edges, lines, contours, or other image attributes of interest such as statistical features) is to reduce the amount of data to form a set of features suitable for further high-level processing. Some intermediate-level operations are also data intensive with a regular processing structure, thus making them suitable candidates for exploiting DLP.

High-level operations interpret the abstract data from the intermediate-level, performing high level knowledge-based scene analysis on a reduced amount of data. These types of operations (for example recognition of objects) are usually characterized by control or branch-intensive operations. Thus, they are less data intensive and more inherently sequential rather than parallel.

2.2 Software Architecture Design

While translating a source code from a research development environment to a real-time environment is an involved task, it would be beneficial if the entire software system is well thought out ahead of time. Considering that real-time image processing systems usually consist of thousands of lines of code, proper design principles should be practiced from the start in order to ensure maintainability, extensibility, and flexibility in response to changes in the hardware or the algorithm [7]. One key method of dealing with this problem is to make the software design modular from the start, which involves abstracting out algorithmic details and creating standard interfaces or application programming interfaces (APIs) to provide easy switching among different specific implementations of an algorithm. Also beneficial is to create a hierarchical, layered architecture where standard interfaces exist between the upper layers and the hardware layer to allow ease in switching out different types of hardware so that if a hardware component is changed, only minor modifications to the upper layers will be needed.

In addition, because in real-time image processing system, certain tasks or procedures have strict real time deadlines, while other tasks have firm or soft real-time deadlines, it is useful to utilize a real time operating system in order to be able to manage the deadlines and ensure a smoothly running system. Real-time operating systems allow the assignment of different levels of priorities to different tasks. With such an assignment capability, it becomes possible to assign higher priorities to hard real-time deadline tasks and lower priorities to other firm or soft real-time tasks [8].

3 Hardware architecture features

There are two classes of digital primary image processing operators: the local operators and the global operators. The global operators require information from the complete image frame. They are not suitable for industrial video applications because they have two main disadvantages: long time execution and edge alteration. On the other hand, many functions like noise rejection, binary segmentation, edge extraction, erosion, dilation, area evaluation, and perimeter evaluation can be calculated by the aid of local bi-dimensional filters. Software implementation of many image processing procedures is not compatible with on-line, real time operation requirements and with hard industrial environment conditions. Moreover, most of the required procedures can be hardware implemented, using programmable devices. Thus, for an efficient industrial image processing system, the hardware/software co-design approach is highly recommended. Operations like noise rejection, edge detection, binary segmentation of image, are frequently encountered.

3.1 Desktop PC platforms

Alongside the developments in hardware architectures for image/video processing, there have also been many notable developments in the application of real-time image/video processing. Relevant technologies include automatic, robust face recognition, gesture recognition, tracking of human or object movement, distributed or networked video surveillance with multiple cameras, etc. Such systems can be categorized as being hard real-time systems and require one to address some difficult problems when deployed in realworld environments with varying lighting conditions.

A great deal of the present growth in the field of image/video processing is primarily due to the ever-increasing performance available on standard desktop PCs, which has allowed rapid development and prototyping of image/video processing algorithms. The desktop PC development environment has provided a flexible platform in terms of computation resources including memory and processing power. In many cases, this platform performs quite satisfactorily for algorithm development. The situation changes once an algorithm is desired to run in real time. This involves first applying algorithmic simplifications and then writing the algorithm in a standard compiled language such as C, after which it is ported over to some target hardware platform. After the algorithmic simplification process, there are different possible hardware implementation platforms that one can consider for the real-time implementation. For the selection of an appropriate hardware platform one must precise what are the important features of an image/video processing hardware platform and its advantages and disadvantages in order to be best suited for the real-time application under consideration.

As discussed in the previous section, practical image/video processing systems include a diverse set of operations from structured, high-bandwidth, data-intensive, low-level and intermediate-level operations such as filtering and feature extraction, to irregular, low-bandwidth, control-intensive, high-level operations such as classification. Since the most resource demanding operations in terms of required computations and memory bandwidth involve low-level and intermediate level operations, considerable research has been devoted to developing hardware architectural features for eliminating bottlenecks within the image/video processing chain, freeing up more time for performing high-level interpretation operations. While the major focus has been on speeding up low-level and intermediate level operations, there have also been architectural developments to speed up high-level operations.

There are two types of General Purpose Processors (GPP) on the market today, one geared toward non embedded applications such as desktop PCs and the other geared toward embedded applications. Today's desktop GPPs are extremely high-performance processors with highly parallel architectures, containing features that help to exploit ILP in control-intensive, high-level image/video operations. GPPs have been outfitted with the multilevel cache feature. This feature provides the potential of having low latency memory accesses for frequently used data. These processors also require an RTOS in order to guarantee a real-time execution. Desktop GPPs are characterized by their large size, requiring a separate chip set for proper operation and communication with external memory and peripherals.

Advances in desktop GPPs have allowed the standard commercial off-the-shelf desktop PCs to be used for implementing non embedded real-time image/video processing systems. In [19] it is even claimed that the desktop PC is the de facto standard for industrial machine vision applications where there is usually enough space and power available to handle a workstation. It should be noted that such systems usually augment the processing power of the desktop GPP with vision accelerator boards. Recently, a paradigm shift toward multicore processor designs for desktop PCs has occurred in order to continue making gains in processor performance.

On the embedded front, there are also several GPPs available on the market today with high-performance general-purpose processing capability suitable for exploiting ILP coupled with low power consumption and SIMD-type extensions for moderately accelerating multimedia operations, enabling the exploitation of DLP for low-level and intermediate-level image/video processing operations.

Both embedded and desktop GPPs are supported by mature development tools and efficient compilers, allowing quick development cycles. While GPPs are quite powerful, they are neither created nor specialized to accelerate massively data parallel computations.

3.2 Graphics Processing Units

The early 2000s witnessed the introduction of a new type of processor, the graphics processing unit (GPU). The primary function of such processors is for real-time rendering of three dimensional (3D) computer graphics enabling fast frame rates and higher levels of realism required for state-of-the-art 3D graphics in modern computer games. While the original GPUs were fixed function accelerators, current generation GPUs incorporate more flexibility through ever-increasing amounts of programmability with programmable vertex and texture/fragment units that are useful for customizing the rendering of 3D computer graphics. In terms of performance, for example, an Intel 3.0-GHz Pentium 4 GPP provides 12 GFLOPS peak floating-point computational performance and 5.96-GB/s memory throughput, while the ATI Radeon X1800XT GPU provides 120 GFLOPS peak floating-point performance with 42-GB/s memory throughput [18]. This shows that GPUs can provide huge increases in GFLOPS

performance and memory throughput over those of a high-performance desktop GPP.
Due to their floating-point calculation capabilities, the increased levels of programmability, and the fact that GPUs can be found in almost every desktop PC today, many researchers have been looking into ways to exploit GPUs for applications other than the real-time rendering of 3D computer graphics, an area of research referred to as general-purpose processing on the graphics processing unit (GPGPU). GPUs have already been deployed to solve real-time image/video processing problems including complete computer vision systems [20], medical image reconstruction in magnetic resonance imaging (MRI) and ultrasonic imaging requiring FFT, stereo depth map computation and subpixel accurate motion estimation at video rates. A relative recent survey paper on the state-of-the-art in GPGPU [21] also presents several examples of how the power of GPUs has been applied to calculation-intensive problems in signal and image processing.

3.3 GPU-Based Systems

GPU-based developments in the field of real-time image/video processing are fairly new, but can be observed in typical examples including stereo depth map computation and subpixel motion estimation. The power of the GPU allowed the use of advanced features, including multiresolution matching, adaptive windowing, and cross-checking. It was stated that better performance gains could be achieved with the newer PCI Express bus. As is shown in [22] GPUs have the potential to solve computationally intensive, data parallel real-time image/video processing problems. The standard use of a GPU is to accelerate computationally intensive operations, leaving the GPP of its host free to handle other tasks. With GPU performance growing at an ever-increasing rate and the introduction of faster bus architectures, such as the PCI Express, the popularity of using GPUs for solving real-time image/video processing problems is expected to increase.
Recently GPUs have become an incredibly powerful computing workhorse for processing computationally intensive highly parallel tasks. Recently Nvidia released the Compute Unified Device Architecture (CUDA) along with the G8800 GPU with a theoretical peak speed of 330 Gflops, which is over two orders of magnitude larger than that of a state of the art Intel processor. This release provides a C-like API for coding the individual processors on the GPU that makes general purpose GPU programming much more accessible. CUDA programming, however still requires much trial and error, and understanding of the nonuniform memory architecture to map a problem onto it.

3.4 PC-Based Systems

PC-based systems have also been widely used for solving real-time image/video processing problems. Such systems are usually equipped with a camera and a frame grabber, using the PC as a host. In the following are presented four examples of such systems, experienced on a test-bed cluster.

3.4.1 Computer Vision System

A computer vision system involves many diverse operations that map well to vision accelerator boards. For example, in [19], a generalized, scalable and modular architecture for a real-time computer vision application based on desktop PCs was presented. The architecture consisted of an image acquisition module and a PC-based processing module, where both modules could be scaled to handle more cameras and higher processing demands. The system was applied to an industrial inspection application involving quality control of TV screen manufacturing.
A more flexible solution is that of the distributed computing for real-time video processing, such as rendering and/or encoding. It is true that distributed computing has mainly been applied to applications in which data could be processed in non-real-time, but one can perform visual communication, if real-time constraints that give additional requirements to data processing in distributed computing are considered. It is necessary to assure the processing time of distributed data since processing period for one frame of video is limited to 1/25 or 1/30 second in most cases. Thus, processing delay is a critical factor for video processing applications especially in the case of non-homogeneous computing environment, such as distributed computing on the Internet.
Distributed computing, which requires universal access to high-grade computation facilities, is yet to be achieved. Average users still suffer from a chronic lack of bandwidth and processing power for demanding applications. Computation complexity and bandwidth necessity make video encoding difficult. Thus, parallel and distributed architectures for video encoding have been the subject of research for the last ten years. Most successful attempts have unfortunately remained in the dominion of those with high performance computers connected by high-speed networks.

Commercial grade video encoding and new, high-quality encoder/decoder are not available to average users. Architecture to distribute and encode video on the Internet would benefit users immensely. It is beneficial to realize state of the art video coding, such as MPEG-4 and AVC (H.264), by distributed computing architecture. It can also be used for the conventional MPEG-2 and MPEG-1 standards. Another application envisaged is the encoding of HDTV and digital cinema, etc. The purpose is to empower the user community to be able to encode and share high quality video without the associated high cost.

Audio and video exchange continues to dominate the traffic on P2P (Peer to Peer) networks today. Media capture, streaming, download, voice and video chat are important applications for the average Internet user. Storage capacity of magnetic hard disks has increased exponentially over the past few years. CPU processing speed has been improved substantially with special instructions for audio and video processing. However, is still that users cannot generate high-quality video on their own, primarily because video encoding has very high computation requirements. Though very good video encoder/decoder abound, normally users cannot easily access to them. Thus, users are stuck with grainy videos captured with low-resolution cameras while commercially excellent HDTV resolution video is available. The video is distributed over the processors available and the encoded video is returned either to the originator or to any other specified machine where it is assembled in to syntactically correct bit stream.

It would be beneficial to design an architecture, which enables high quality video encoding over open networks like the Internet. This approach would enable common users to make use of high quality video encoder/decoder and encode high-resolution videos irrespective of the bandwidth constraints. To design such architecture, it is necessary to take a look at distributed computing in general and grid computing in particular [25].

The idea is to be able to share resources at will - computers, storage, sensors, networks, etc. This takes the concept beyond standard client-server with distributed data analysis, computation, and collaboration aided by the creation of large or small, static or dynamic, multi-institutional virtual organizations.

What this translates into for distributed video encoding is that the number of processors (machines) available may vary not only from session to session but also during the session itself. Second, the processors may have varying characteristics, processing capabilities and instruction sets. Third, there are no guarantees regarding the time that will be taken to complete a job, or whether it will be completed at all. Fourth, the links between the processors may each have different characteristics and capacities. Considering the special requirements for computation over grids, we can design architecture quite different than what is used for simple parallel encoding on a cluster of networked PCs.

3.4.2 Video Segmentation System

Another computationally complex problem involves real-time segmentation of video data. It has been shown in [23] that such a system can be implemented using off-the-shelf components without the need for high-end and expensive frame grabbers. In this reference, the problem of image sequence segmentation based on a global camera motion compensation, a robust frame differencing, and a curve evolution was discussed. The segmentation performance achieved was 5 fps for 160 × 120 images, keeping in mind that the implementation was done on a rather slow GPP.

3.4.3 Image Fusion System

Another example involving the successful use of a vision accelerator board is reported in [24], where an adaptive image fusion algorithm was implemented to aid helicopter pilots. The real-time requirement of processing 256 × 256 images at 25 fps for image registration and a three-level pyramid decomposition was met using a hybrid hardware and software approach. As revealed from this example, standard desktop PCs equipped with frame grabbers can be used to solve real-time image/video processing problems. Due to their large size and high power consumption, however, such systems are usually used in industrial inspection settings or those applications where size and power consumption are not critical design issues.

3.4.4 Object Detection System

Object detection is a computationally complex problem, requiring a high-performance processor for practical implementations. In [24], the problem of object detection in real-time was discussed. A point was made that while VLSI, ASIC, or FPGAs can be used to meet the real-time constraint for video rate object detection, such solutions require a low-level hardware design that is often difficult to achieve by image processing developers unfamiliar with design techniques. Thus, it was decided to use the Datacube MaxPCI vision accelerator board that provided the necessary parallel computation power and high data throughput to process 1000 × 1000 images at 30 fps.

4. Performing real time image processing on a distributed platform

4.1 Parallel platform model and scheduling principles

Our system model consists of P processor units. Each processor p_i has capacity $c_i > 0$, $i = 1,2,\dots, P$. The capacity of a processor is defined as its speed relative to a reference processor with unit-capacity. We assume for the general case that $c_1 \le c_2 \le \dots \le c_P$. The *total capacity* C of the system is defined as $C = \sum_{i=1}^{P} c_i$. A system is called *homogeneous* when $c_1 = c_2 \dots = c_P$. The platform is conceived as a distributed system [9]. Each machine is equipped with a single processor. In other words, we do not consider interconnections of multiprocessors. The main difference with multiprocessor systems is that in a distributed system, information about the system state is spread across the different processors. In many cases, migrating a job from one processor to another is very costly in terms of network bandwidth and service delay [10], and that the reason that we have considered for the beginning only the case of data parallelism for a homogenous system. The intention was to test the general case of image processing with both data and task parallelism, by developing a scheduling policy with two components [11]. The *global* scheduling policy decides to which processor an arriving job must be sent, and when to migrate some jobs. At each processor, the *local* scheduling policy decides when the processor serves which of the jobs present in its queue.

Jobs arrive at the system according to one or more interarrival-time processes. These processes determine the time between the arrivals of two consecutive jobs. The *arrival time* of job j is denoted by A_j. Once a job j is completed, it leaves the system at its *departure time* D_j. The *response time* R_j of job j is defined as $R_j = D_j - A_j$. The *service time* S_j of job j is its response time on a unit-capacity processor serving no other jobs; by definition, the response time of a job with service time s on a processor with capacity c' is s/c'. We define the *job set* $J(t)$ *at time* t as the set of jobs present in the system at time t:

$$J(t) = \{ j \mid A_j \le t < D_j \}$$

For each job $j \in J(t)$, we define the *remaining work* $W_j^r(t)$ *at time* t as the time it would take to serve the job to completion on a unit-capacity processor. The *service rate* $\sigma_j^r(t)$ *of job j at time t* ($A_j \le t < D_j$) is defined as: $\sigma_j^r(t) = \lim_{\tau \to t} \frac{dW_j^r(\tau)}{d\tau}$. The *obtained share* $\omega_j^s(t)$ *of job j at time t* ($A_j \le t < D_j$) is defined as: $\omega_j^s(t) = \sigma_j^r(t)/C$. So, $\omega_j^s(t)$ is the fraction of the total system capacity C used to serve job j, but only if we assume that $W_j^r(t)$ is always a piecewise-linear, continuous function of t. Considering $W_j^r(A_j) = S_j$ and $W_j^r(D_j) = 0$ we have $\int_{A_j}^{D_j} \omega_j^s(t)dt = \int_{A_j}^{D_j} \sigma_j^r(t)dt = S_j / C \cdot$

One can define an upper bound on the sum of the obtained job shares of any set of jobs {1,…,J}as:

$$\omega_{\max}(t) = C^{-1} \sum_{i=1}^{\min(J,P)} c_i .$$

4.2 A case study: lines detection

4.2.1 Theoretical background

Usually the problem of detecting lines and linear structures in images is solved by considering the second order directional derivative in the gradient direction, for each possible line direction [12]. Theoretically, in two-dimensions, line points are detected by considering the second order directional derivative in the gradient direction. For a line point, the second order directional derivative perpendicular to the line is a measure of line contrast, given by $\lambda = f_{ww}(x,y)$ where $f(x,y)$ is the grey-value function and the indices w denote differentiation in the gradient direction. Bright lines are observed when $\lambda < 0$ and dark lines when $\lambda > 0$. In practice, one can only measure differential expressions at a certain observation scale. By considering Gaussian weighted differential quotients in the gradient direction, $f_{ww}^{\sigma} = G_{ww}(\sigma) * f(x,y)$, a measure of line contrast is given by $r(x,y,\sigma) = \sigma^2 \left| f_{ww}^{\sigma} \right| \frac{1}{b^{\sigma}}$ where σ,, the Gaussian standard deviation, denotes the scale for observing the line structure, and where line brightness b is given by

$$b^{\sigma} = \{ \begin{array}{l} f^{\sigma} if \dots f_{ww}^{\sigma} \le 0 \\ W - f^{\sigma} otherwise \end{array}$$

Line brightness is measured relative to black for bright lines, and relative to white level *W* (255 for an 8-bit camera) for dark lines [13].

The response of the second order directional derivate λ does not only depend on the image data, but it is also affected by the Gaussian smoothing scale *σ*. Because a line has a large spatial extent along the line direction, and only a small spatial extent (i.e., the line width) perpendicular to the line, the Gaussian filter should be tuned to optimally accumulate line evidence. For directional filtering anisotropic Gaussian filters may be used of scale σ_v and σ_w, for longest and shortest axis, respectively. Line contrast is given by:

$$r'(x,y,\sigma_v,\sigma_w) = \sigma_v\sigma_w \left| f_{ww}^{\sigma_v,\sigma_w} \right| \frac{1}{b^{\sigma_v,\sigma_w}}$$

The optimal filter orientation may be different for each position in the image plane, depending on line evidence at the particular image point under consideration. The final line detection filter, parameterized by orientation θ, smoothing scale σ_v in the line direction, and differentiation scale σ_w perpendicular to the line, is given by

$$r''(x,y,\sigma_v,\sigma_w,\theta) = \sigma_v\sigma_w \left| f_{ww}^{\sigma_v,\sigma_w,\theta} \right| \frac{1}{b^{\sigma_v,\sigma_w,\theta}}$$

where $f_{ww}^{\sigma_v,\sigma_w,\theta} = G_{ww}(\sigma_v,\sigma_w,\theta) * f(x,y)$

When the filter is correctly aligned with the line, and σ_v, σ_w are optimally tuned to capture the line, filter response is maximal. Hence, the maximum per pixel line contrast over the filter parameters yields line detection:

$$R(x,y) = \arg\max_{\sigma_v,\sigma_w,\theta} r''(x,y,\sigma_v,\sigma_w,\theta)$$

The final result is obtained by considering the maximum response per pixel over all filter results. This yields the optimal orientation *θ,* an estimate of line thickness σ_w, the best smoothing size σ_v, and the line contrast *R(x,y).*

4.2.2 Software implementation of the directional filtering algorithm

There are many different ways to implement a directional filtering algorithm. For example, one can create for each orientation a new filter based on σ_v and σ_w. This yields a rotation of the filters, while the orientation of the input image remains fixed. Another possibility is to keep the orientation of the filters fixed, and to rotate the input image instead. Yet another solution is to integrate the notion of orientation in the filter operation itself. In this case image pixels are accessed not only according to the size of the neighborhood of the filter, but also on the basis of the given orientation [14]. From these solutions, the second, who consists in applying fixed filters to rotated image data, seems to be more suitable for parallelization. In order to stress the possibility to execute parallel operations, let consider first the main steps of a sequential implementation.

The first step consists in rotating the original input image for a given orientation *θ.* This operation is made by a dedicated routine *Rotate_Image*. Then, for all combinations *(*σ_v, σ_w*)* the filtering is performed by six operations executed in sequence by six dedicated routines, as follows: 1) *Filter 1* to compute $f_{ww}^{\sigma_v,\sigma_w,\theta}$; 2) *Filter 2* to compute $b^{\sigma_v,\sigma_w,\theta}$ (both filtering operations are generalized Gaussian convolutions performed by applying two 1-dimensional filters; 3) *Binary_Op1*, a binary pixel operation having an image as argument; 4) *Binary_Op2*, a binary pixel operation having an constant value as argument; 5) *Back_Rotate_Image* to match the orientation of the original input image; 6) *Contrast* to obtain the maximum response.

It is to note that on a state-of-the-art sequential machine the program may take from tens of seconds up to minutes to complete, depending on the size of the input image and the extent of the chosen parameter subspace. Consequently, for the directional filtering program parallel execution is highly desired.

The above described program may be processed in parallel in two different schedules. In the first schedule all dedicated routines are forced to run in parallel, using all available processing units. The second schedule differs from the first in that the last two operations in the innermost loop of the program are run on one node only. In both schedules the *Original_Image* structure must be broadcast to all nodes. This is because the structure is applied in the initial rotation operation. In addition, in both schedules the first four operations in the innermost loop can be executed locally on partial image data structures. The only need for communication is in the exchange of image borders (shadow regions) in the two Gaussian convolutions.

In the first schedule the last two operations in the innermost loop are run in parallel as well. This requires the distributed image *Binary_Op1* to be available in full at each node, because it has an access pattern of type 'other' in the back-rotation operation. This can be achieved by executing a gather-to-all operation, which is logically equivalent to a gather operation followed by a broadcast. Finally, a partial maximum response image *Contrast* is calculated on each node, which requires a final gather operation to be executed just before termination of the program. In the second schedule the last two operations are not executed in parallel. As a result, the intermediate result image after *Binary_Op2* that produces both the back-rotated image needs to be gathered to the single node, as well as the complete maximum response image.

4.2.3 Experimental results

A test image was processed first on a single processing unit, then on a test network configured as a cluster with 2, 4 or 8 nodes, each node being a processor unit working at 1 GHz with 128 MByte RAM. For each instruction utilized in the directional filtering algorithm two measurements were executed, for images having 200^2 or 1000^2 elements. Table 1 offers the measured results for the processing times of an image with 1024x1024 pixels (see fig. 2: a) original, b) after processing with 12 orientations and 4 combinations (σ_v, σ_w).

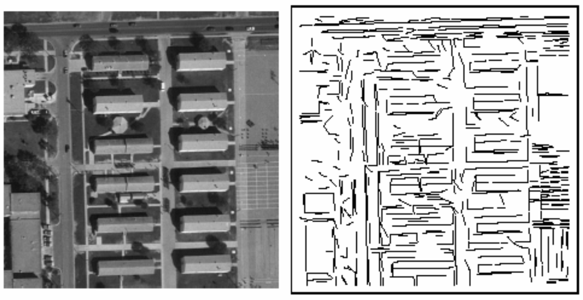

Fig. 2. Test image for line detection

Table 1. Comparison of processing times for different cluster dimensions

Number of processors	Measured duration [s]	
	Schedule 1	Schedule 2
1	5.56	5.56
2	2.90	4.01
4	1.60	3.22
6	0.97	2.82
8	1.21	2.95

A schedule is preferred if the set of operations unique to that schedule is faster than the set of operations unique to another schedule (i.e., not in the set of operations common to both schedules). Hence, for the directional filtering program the schedule in which *all* operations are run in parallel is preferred if:

$$\theta_\sigma(P_{rotate}(size/N)+P_{max}(size/N)+P_{bcast}(size/N)+P_{gather}(size/N)) < \theta_\sigma(P_{rotate}(size)+P_{max}(size))$$

where N denotes the number of processing units and θ_σ denotes the size of the parameter subspace. For the first schedule the large number of broadcast operations is expected to have the most significant impact on performance. For the second schedule, on the other hand, the many rotations of non-partitioned image data are expected to be costly. Another difference between the two schedules is the fact that the total duration decrease proportional with the number of nodes only for schedule 2. For the schedule 1 there is an optimal structure with 6 nodes, then when the number of nodes is grater the processing duration begins to rise again.

5 Conclusions

The experiments show how to use parallelizable patterns, obtained for typical low level image processing operations. In our study case the performance model is highly accurate for parallel processing using convolution functions. Given the results we are confident in that the proposed software architecture forms a powerful basis for automatic parallelization and optimization of a wide range of image processing applications.

Regarding the potential of the parallel platform for image processing, in the near future we will focus our attention on the improvement of the scheduling component, by using processor units with different processing capacities and also other service policy for the queue of jobs. We will continue implementing example programs to investigate the implication of parallelization of typical applications in the area of real-time image processing, trying to improve the performances by supporting the execution of a sequence of algorithms on the same block and by dynamical reconstruction of the post processed image.

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