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A DISTRIBUTED IMAGE PROCESSING FUNCTION SET FOR AN IMAGE MINING SYSTEM

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Abstract.
An Image Mining System (IMS) requires real time processing often using special purpose hardware. The work herein presented refers to the application of cluster computing for on line image processing inside an IMS, where the end user benefits from the operation on data with a high degree locality and parallelism. The virtual parallel computer is composed by a cluster of personal computers connected by a low cost network. The aim is to minimise the processing time of a high level image processing package. The image processing function set developed to manage the parallel execution is described and some results obtained from the parallelisation of image processing algorithms are discussed.

1 INTRODUCTION

With the advances in multimedia data acquisition and storage techniques, the need for automatic knowledge discovery from large image collections is becoming more and more relevant.

Automatic image categorization tries to simulate how human visual system manages visual contents of images and categorizes them. The aim is to build a model using attributes extracted from and attached to stored images, then evaluating the effectiveness of the model by new images. Image mining deals with the study and development of new technologies that allow accomplishing this subject.

A common mistake about image mining is identifying its scopes and limitations. Clearly it differs from computer vision and image processing areas. Besides, image mining is not data mining on images. Moreover, many knowledge discovery algorithms defined in data mining context are ill-suited for image mining.

In addition an image mining have to deal with all aspects of large image databases including image storage, indexing schemes, and image retrieval, all concerning a single system (Missaoui and Palenichka (2005)). Image databases containing raw image data as information, cannot be directly used for image mining purposes. The big challenge in image mining is extracting implicit knowledge, image data relationships, or other features not explicitly stored in a pixel representation. There exist many investigations in the area, trying to discover useful image patterns for the understanding of existing interactions between image human perception at high level and image features at low level (Keiji (2003); Selim et al. (2004); Wang et al. (2004)).

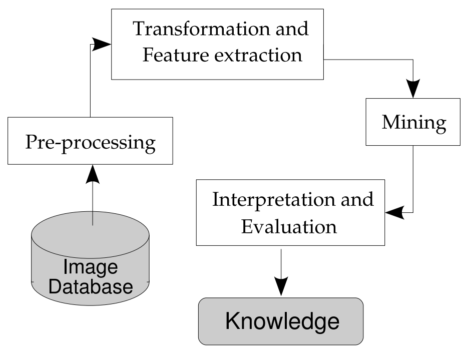

Figure 1: General Image Mining System.

Figure 1 shows a general structure model for an image mining system. The system considers an specified amount of stored images, whose image features had been extracted to represent concisely their image content -***Transformation and feature extraction phase***-. Besides the relevance of this task, it is essential to consider the invariance problem to some geometric transformations and robustness with respect to noise and other distortions before designing a feature extraction operator -***Pre-processing phase***-. After the transformation and feature extraction phase, a *model description* representing a correct semantic image interpretation is obtained.

Mining phase leads to describe new association rules for the stored complex information while ***Interpretation and Evaluation phase*** tries to generate all significant patterns without any knowledge of the image content.

Query decisions are based on a given *symbolic description* of searched image content. The symbolic description might be just a feature or a set of features, a verbal description or phrase in order to identify a particular semantic. Image mining results are acquired after matching the symbolic description with its complementary model description and the corresponding discovered knowledge relationships.

Finally, the development of an image mining system is often a complex process since it implies joining different techniques ranging from data mining and pattern recognition up to image retrieval and indexing schemes. Besides, it is expected that a good image mining system provides users with an effective access into the image repository at the same time it recognizes data patterns and generates knowledge underneath image representation. Such system basically should assemble the following functions: *image storage*, *image pre-processing*, *feature extraction*, *image indexing* and *retrieval* and, *pattern* and *knowledge discovery*. There exist still many challenges to be overcome, including data complexity, scalability, data inaccessibility, privacy, minor support and insufficient training. Solving them in only one good application could be hard or impossible, but independent treatment of anyone could give notorious improvements to the whole image mining process.

As a result, an image mining system implies lots of tasks to be done in a regular time. Images provide a natural source of parallelism; so the use of parallelism in every or some mining tasks might be a good option to reduce the cost and overhead of the whole image mining process. There exist some approaches that define a parallel model and analyse their theoretical performance cost (A. Mazurkiewicz (2002); Fernandez et al. (2007a,b)).

This works is structured as follows: the next section explains the three main stages constituting a standard image mining system and their feasibility to be parallelized. Section 3 states the adopted IMS parallel model. Section 4 introduces the "*what*" and "*where*" systems of and IMS processing stage. Last sections describe the high performance function implementations related to the introduced "*what*" system and some conclusions about their computations.

2 PARALLELISM INTO AN IMAGE MINING

Many issues of image mining can be optimized with different parallel techniques. Furthermore depending on properties of the tasks, different parallel paradigms could be applied in the same system. At a first glance, parallel applicant tasks will be: image storage, image processing (pre-processing and feature extraction), mining (pattern and knowledge discovery) and interpretation/evaluation (image indexing and retrieval). In this section, the three main stages of an image mining system will be explained and the feasibility of apply parallel paradigms.

2.1 Processing Phase

Since real-life data is often incomplete, noisy and inconsistent, pre-processing becomes a necessity enabling data cleaning by removing noise or other aspects that could mislead the actual mining process. This image enhancement helps in qualitative improvement of the image and can be done either in the spatial domain or in the frequency domain. The most common techniques applied for data cleaning are typical image processing techniques like smoothing and sharpening filters. All these techniques could be combined with respect to a specific application.

Following pre-processing, feature extraction task implies data transformation to get an image content descriptor based on its visual and semantic content. Visual content can be very *General* (color, texture, shape, spatial relationships, among others) or *Domain specific* (application dependent and may involve domain knowledge). A good visual content descriptor should be invariant to any accidental variance introduced by the imaging process. A visual content descriptor can be either *Global* or *Local*. Global descriptors use the whole image visual features, whereas Local descriptors use the visual features of *regions* or *objects* describing the image content. Usually, local descriptors imply dividing the image into tiles of equal size and shape. A simple partition does not generate perceptually meaningful regions but is a way of representing the global features of the image at a finer resolution. Some widely used techniques for extracting General content features are: Color Moments, Color Histograms, Color Coherence, Color Correlogram, Gabor Filter, Tamura features, Wavelet Transform, Moment Invariant, Turning Angles, among others (Gonzalez and Woods (2002); Parker (1997)).

Semantic content could be obtained by textual annotation or by complex inference procedures based on visual content. We will not discuss in detail this topic, trying to focus on our subject.

Figure 2 shows an overview of a categorization process. The first step is represented the image acquisition and image enhancement, followed by feature extraction. The last one is the classification step, where different techniques for supervised learning are applied.

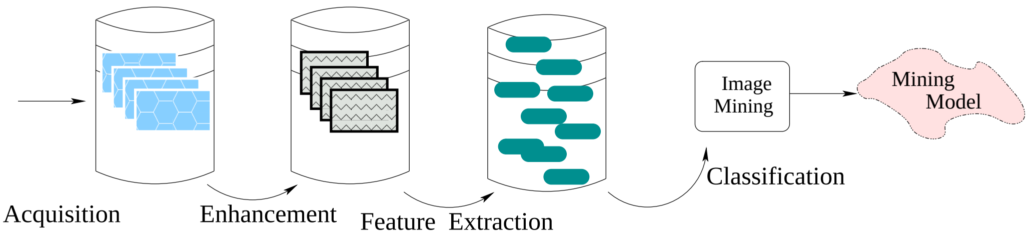

Figure 2: Image categorization process

Orthogonal to challenges of developing specific image mining algorithms and models that operate on idiosincrasy of images, the major challenge for image mining is the pre-processing state previous to the extraction of relevant features. Generally, most of the images, if not all, are difficult to interpret, and the pre-processing phase is necessary to improve the quality of the images and make the feature extraction phase more reliable. The pre-processing state is arguably the most complex phase of the knowledge discovery process when dealing with images. If the pre-processing is well done, it can be decisive whether patterns could be discovered, or whether the discovered patterns could be interpreted at all. This phase often requires related expertise to computer vision, image processing, image interpretation, graphics and signal processing, domain knowledge or domain applications, most of them are natural sources of parallelism (T. Braunl (2001)).

2.2 Mining Phase

In the nontrivial process of knowledge discovery in databases, data mining in general, and image mining in particular, have the aim of extracting implicit knowledge from data. They try to define valid, novel, potentially useful, and ultimately understandable patterns, relations or rules from them. These relations draw a *Predictive* or *Descriptive* model. With a predictive model is possible to estimate future or unknown values of interest, while with a descriptive model is possible to identify patterns which explain or summarize the analized data. Mining tasks depend in the model to be applied. *Classification* or *Regression* techniques define predictable models, while *Association Rule Mining* or *Clustering*, among others, define descriptive models.

As image mining refers to a set of methods dedicated to the extraction of hidden knowledge from within an assortment of images, the early image miners have adopted existing machine learning and data mining techniques to mine for image information. As a result, very few achievements have been obtained and the approaches can be grouped into two classes. Those that discover patterns from:

- Images in large collections using the processed and extracted features within images;
- The image database using general descriptors.

While applications fluctuate from creating suitable models for image indexing, to recognizing objects, categorizing images or image segments, general tasks are similar and can be summarized as grouping images or features, either supervised or unsupervised, and associating image features. Techniques frequently used include object recognition, image classification and clustering, association rules mining and neural network or a any combination of them. The use of parallelism in an isolate way for every one of this techniques had been tried (Skillicorn (1999); Djeraba (2003); Orallo et al. (2004)), it remains an analysis of a parallel combined use of them.

2.3 Interpretation and Evaluation Phase

This is an important task because it is tightly related with mining phase because it measures the quality from obtained patterns. Model preciseness can be secured by guarantying data independency between the training data set and testing data set.

Different evaluation techniques and measures can be applied. Evaluation measures could be *Objective* or *Subjective*. Which one of them would be used will depend on the mining tasks to be done. The application context should be always considered when validating the obtained model (Orallo et al. (2004); Keiji (2003)). Any parallel implementation of this phase is very challenge because it depends on the domain application and is strongly tightly to user validation.

3 IMS PARALLEL MODELS

An Image Mining System (IMS) can be very computationally demanding due to the large amount of data to be processed, the required response time or the involved image processing algorithms complexity. Any parallel system requires dividing up the work so that processors can make useful progress towards a solution as fast as possible. The main challenge is: *how to divide the labor*.

There are three components to the work: computation, data set access, and communication among processors (A.Grama et al. (2003); Gou and Yang (2006)). These components are tightly related: dividing up the computation to make it faster creates more communication and often more data set accesses as well. Finding the best parallel algorithm requires carefully balance of the three named issues.

An image mining system could be accomplished by assorted parallel strategies. In Fernandez et al. (2007a,b) some models were proposed varying from a Global Parallel one thru a combination of different Local Parallel Models focusing on the pre-processing stage. Here we will concentrate on the advantages got from the referred work. In particular we will focus on the local parallel model which takes into account parallelism depending on image processing tasks.

At this level any parallel model proposed not depends directly from the mining model itself, whereas it depends directly from any image processing task involved at the processing phase. As a consequence, any possible parallel model will be closely related to the specific image processing task to be done (Gonzalez and Woods (2002)). The best solution could be to build a standard parallel image processing library that enables to make parallel processing at different combinations.

4 PROCESSING FUNCTIONS

An image mining systems claims acting like a human visual system. Visual perception concerns the acquisition of knowledge - this means that vision is fundamentally a cognitive activity, distinct from purely optical processes such as photographic ones.

At earlier stages, a human visual system is involved in identifying objects and in locating objects. These two pathways are often called the "*what*" system and the "*where*" system, respectively. In 1988, Livingstone and Hubel (1988) proposed a hypothesis about how different visual information is processed in different neural pathways from the retina onward. The hypothesis stated separate neural pathways for processing information related to different visual properties such as *color*, *shape*, *depth*, and *motion*. The color and shape properties may project to the "*what*" system for object identification and the depth and motion properties to the "*where*" system for object localization. Now it is abundantly clear that a great deal of visual processing takes place in parallel across different subregions of visual cortical areas and finally they get together somewhere in the brain.

A sort of standard image processing tasks are commonly used at processing phase, like image smoothing, histogramming, 2-D FFT calculation, local area histogram equalization, local area brightness and gain control, feature extraction, maximum likelihood classification, contextual statistical classification, scene segmentation, clustering feature enhancement, among others (Choudhary and Ranka (1992)). There exist many algorithmic implementations (Ballard and Brown (1982); Beucher and Meyer (1993); Crespo et al. (1995); Giardina and Dougherty (1988); Jahne (1997); Jain (1989)) for those tasks that could be done thru parallel solutions. Moreover, different techniques at different grain scale could be applied depending on the particular task (Barbosa and Padilha (2000); T. Braunl (2001); Vorontsov (1999)).

As it was stated, these image processing tasks must be classified into the four types of information to be obtained, be done in parallel, and at the end be combined to enable the construction of a descriptive feature vector at the feature extraction stage.

At this paper, we will focus on the "*what*" system, trying to organize the most commonly used image processing tasks for the extraction of color and shape information, to run them in parallel, and at last to combine them into a unique system.

4.1 Color Information

Color is a psycological phenomenom, a subjective experience depending on the combined characteristics of three element: the light emitting source, the observed object, and the observer' s visual system.

Color space is the benchmark used to define the colors of an image. There exist different ways to define a color space (J.D.Foley et al. (1990)). Thinking about RGB color space containing n colors (RGB^n), the color features of an image I in this color space could be describe as $RGB^n(I) = \bigcup_{i=1}^{n}(r_i, g_i, b_i)$, where r_i, g_i, b_i are the ith color value of the component Red, Green and Blue, respectively.

There exist at the bibliography many ways to operate color characteristics of pixels in order to define an image descriptor (Burl (1999); Lee and Street (2001); Tan et al. (2001)). All of them use a specific color space. The color space in conjunction with the selected operation will strongly influence the final image descriptor. The most commonly used color treatment methods are: color histogram, color moments, color coherence, and color correlograms. Here we will advocate to the first one.

4.1.1 Histogram

Color histogram is the color's statistical information of an image at a given color space.

In RGB^n color space, let I be an $N \times M$ image, its color histogram is a vector as following

$$H(I) = (h_{c_1}(I), h_{c_2}(I), \ldots, h_{c_i}(I), \ldots, h_{c_n}(I))$$

where, $c_i = (r_i, g_i, b_i) \in RGB^n(I)$, and the component $h_{c_i}(I)$ is the number of pixels of a given color c_i in the image I and $\sum_{j=1}^{n} h_{c_j}(I) = N \times M$

According to color histogram definition, the frequency of each color is relevant to the given image size. In order to eliminate the effect of image size on the specification of an image feature, it needs normalizing each component $h_{c_f}(I)$ of $H(I)$ by image size. Thus, $h_{c_i} \in [0, 1]$, and is not affected by the image size. Thus, color histogram is a discrete representation of image appearances. With it, similarity among images can be expediently computed.

In most of the known color spaces, image colors are represented in the form of a 3D vector. In RGB^n color space, axis $R, G,$ and B have 256 discrete color values. Hence, the color histogram of an image is a $256 \times 256 \times 256$ dimensional vector in RGB^{256} color space.

As it is well known, if the number of colors of an image is too large, it will exceed human's visual capacity. Thus, without sacrificing the representation precision and taking advantage of human's visual capacity, the number of dimension of each axis can be reduced, for example the axis R and G into 8 bins, and the axis B into 4 bins. In this way, the former $256 \times 256 \times 256$ feature vector is reduced into $8 \times 8 \times 4$ feature vector.

In this work, we present the two mentioned implementations of color histogram calculation: Full Color Histogram (FCH) and bins color histogram or Mean Value Histogram (MVH). In section 5 we show implementation details and some results.

4.2 Shape Information

Edges characterize object boundaries. Edges are visually important to human beings in recognizing or perceiving the shape of objects. Edge detection is a problem of fundamental importance in image analysis, therefore useful for segmentation, registration, and identification of objects in a scene.

An edge is a jump in intensity and an ideal edge is a discontinuity. An edge detection strategy can be expressed in terms of the derivatives of the continuous image $I(x, y)$. In practice, finite difference approximations of first and second order directional derivatives are used. These are represented by discrete masks formally embodying linear-phase FIR filters that convolve with the image.

To recover the edges, the convolved image must be segmented using a global or local (i.e., adaptive) threshold operator. The choice of a threshold value determines the resulting segmentation and, therefore, the perceived quality of the edge detector. It is useful to consider the cumulative histogram of the convolve image in selecting an appropriate threshold value.

Substantial research has been made on image processing methods on edge detection (Gonzalez and Woods (2002)). Here we will analyse the most common first-order edge operators: Robert, Prewit, and Sobel and second-order edge operator: Laplacian of a Gaussian. In section 5 we show implementation details and some results for the first-order edge operators.

4.2.1 Robert Operator

Roberts' Cross operator is one of the earliest edge detection algorithms. This can be accomplished by convolving the image with two 2×2 kernels (Fig. 3). Roberts' Cross is still in use due to the speed of computation, but performance compared to the alternatives is poor, with noise sensitivity a significant problem.

0	1
-1	0

(a)

1	0
0	-1

(b)

Figure 3: Robert's masks.

4.2.2 Prewit Operator

Prewitt operator uses two 3×3 kernels (Fig. 4) which are convolved with the original image to calculate approximations of the derivatives -one for horizontal changes, and one for vertical-. Although differential gradient edge detection needs a rather time-consuming calculation to estimate the orientation from the magnitudes in the x- and y-directions, the Prewitt edge detection obtains the orientation directly from the kernel with the maximum response.

-1	-1	-1
0	0	0
1	1	1

(a)

-1	0	1
-1	0	1
-1	0	1

(b)

Figure 4: Prewit's masks.

4.2.3 Sobel Operator

Sobel operator is based on convolving the image with a small, separable, and integer valued filters in horizontal and vertical (Fig. 5). Each Sobel edge mask is a combination of a digital differentiator in one of the spatial directions and a smoothing operator in the other. The result therefore shows how "abruptly" or "smoothly" the image changes at that point, and therefore how likely that part of the image represents an edge, as well as how that edge is likely to be oriented.

-1	-2	-1
0	0	0
1	2	1

(a)

-1	0	1
-2	0	2
-1	0	1

(b)

Figure 5: Sobel's masks.

4.2.4 Laplacian of a Gaussian Operator

A zero-crossing edge operator ($LoG(x, y)$) originally proposed by Marr and E.Hildreth (1980). In order to effectively detect intensity changes (edges), the operator needs to have two characteristics. First, it must be a differential operator, taking either a first or second spatial derivative of the image. Second, it should be capable of being tuned to act at any desired scale so that large filters can be used to detect blurry shadow edges, and small ones can be used to detect sharply focused fine details in the image. The so-called Laplacian-of-Gaussian edge operator is a compound operator that combines a smoothing operation (Gaussian-shaped filter, G), with a differentiation operation (discrete Laplacian, ∇^2). Edges are identified by the location of zero crossings. The resulting operator is defined for every pixel (x, y) of the image I as stated by the following formulae and implemented by the composition of the two kernels of Figure 6.

0	-1	0
-1	4	-1
0	-1	0

(a)

1/16	1/8	1/16
1/8	1/4	1/8
1/16	1/8	1/16

(b)

Figure 6: (a) Laplacian, (b) Gaussian masks.

$$LoG(x, y) = \nabla^2(G(x, y)I(x, y)) \qquad where\ \nabla^2 = \frac{\partial^2}{\partial x^2} + \frac{\partial^2}{\partial y^2} \quad and\ G(x, y) = \frac{e^{-\frac{x^2+y^2}{2\sigma^2}}}{2\pi\sigma^2}$$

5 HIGH PERFORMANCE COMPUTING VERSIONS

When talking about cluster of computers as parallel architecture, it is necessary to keep in mind their characteristics: distributed memory and high communication costs. The working methodology of the BSP computation model fits adequately to this architecture type.

Parallel versions for each processing function were implemented following the BSP computation model. Every solution involves an only super step. The resulting computations follow the SPMD paradigm (SIMD generalization) with a *worker pool* scheme with *coordinator*. At each implementation, the incoming image is partitioned into stripes, one for each worker. The workers calculate the corresponding processing function for the assigned image slices. Finally, one worker takes the coordinator rol and joins the processed image slices.

For color information, the two presented versions of histogram were parallelized: the whole color image space histogram ($256 \times 256 \times 256$) and the posterized image version ($8 \times 8 \times 4$). The second implementation could be thought as a combination of two processing steps, a posterize step and a histogram step.

For shape information, every edge detection parallel implementation must takes into account pixel's correlation to establish image strip sizes. The calculus of the sizes of stripes must takes into account overlapping because the idiosyncrasy of the calculus.
Figure 7 shows an example image of the testing image set. Three different image sizes were applied: small (379×395), medium (2592×1944) and large (4096×5716). Results were obtained from a 12 networked nodes cluster, each node consisting on a 32 GHz Pentium IV with 1Gb Ram. Nodes are connected together by Ethernet segments and Switch Linksys SRW 2024 of 1Gb. Base software on cluster includes a Debian Etch SO and MIPCH 2.1.0.6. Following images show the different speedup got from the referred implementations. Under the specifications and the solution stated for the full color histogram problem, any improvements are obtained by the parallel version. No matter the image size used, settlement of different slice sizes for full color histogram calculation do not reduce the combination cost of local histogram slices.

Figure 7: Original Image.

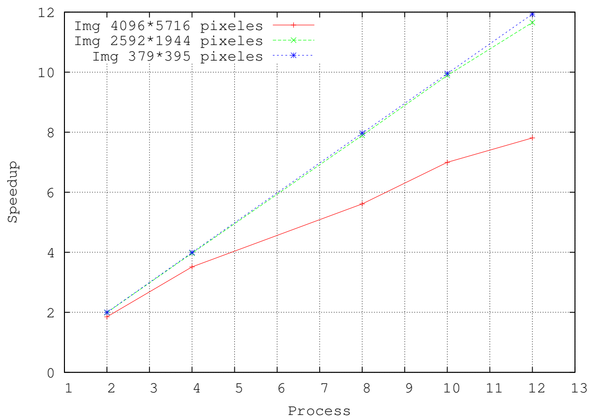

Figure 8: Original Image.

Figure 8 shows the speedup obtained by the mean value histogram applied to the three tested image sizes. It could be observed high profits and the influence of the communications and data combination in respect to the image size.

Figure 9 presents the relationships between the two calculated histogram times. Here it is represented the high computational cost got from the full color histogram on account of the not required visual color information given to the whole image mining system.

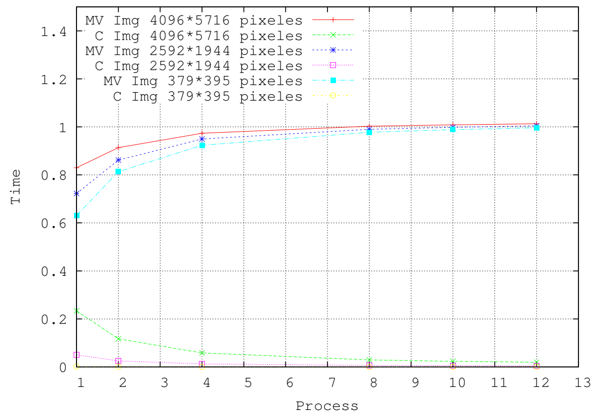

Figure 9: Mean Value Histogram versus Complete Histogram times.

Figures 10 shows performance obtained by the different edge operators. It can be pointed out that better results are gotten by those operators that require more computational calculus (See Fig. 10(c)). From this observation, the same behavior could be predicted for the Laplacian of the Guassian filter.

6 CONCLUSIONS

In this report we have summarized concepts about an image mining system, the most important issues involved in IMS stages and the human visual system characteristics related to the processing stage.

We had illustrated how high performance computing techniques can be applied into a cluster of computers providing a parallel solution to general image mining problems thru a parallel image processing function set. Selected functions are among the most commonly used to simulate the human visual processing system in an isolate or combined form. Some specific application results had been analyzed.

According to this, any feature in conjunction with other features and a corresponding distance measurement, similarity among different images could be obtained, and content based image retrieval could be done. This has a whole application into an MIMD parallel paradigm. Future studies will be oriented to extend image processing function set and to integrate them in conjunction with the referred MIMD paradigm.

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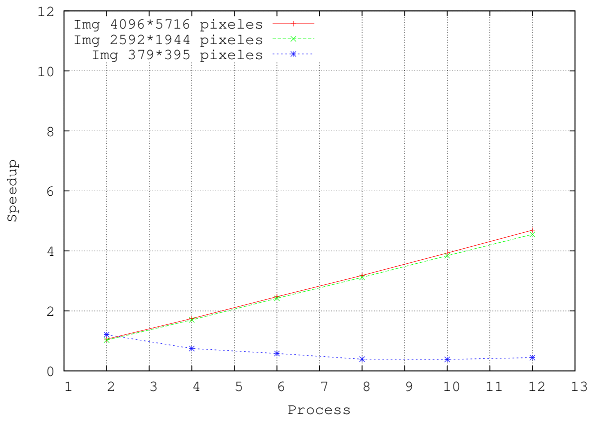
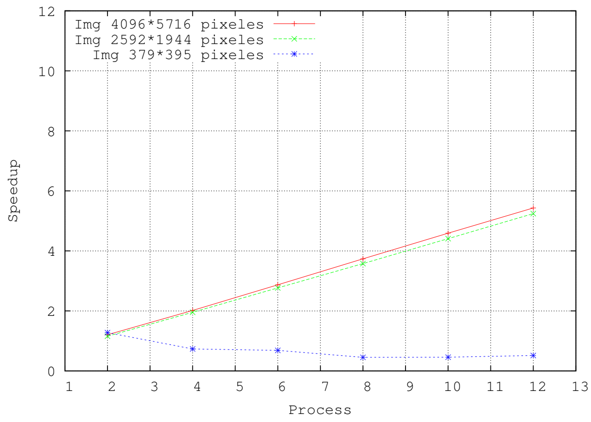
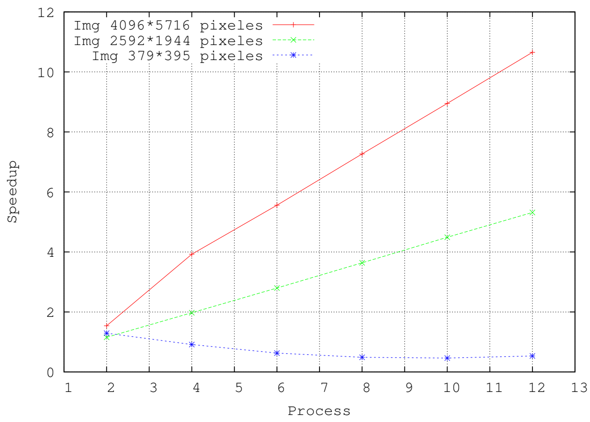


(a) Robert



(b) Prewit



(c) Sobel

Figure 10: Speedup of Edge Detection.

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