Parallel Algorithms for Using Non-stationary MRA in Image Compression

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Abstract. New methods for compact image coding based on generalized wavelet decompositions have been introduced recently. Unlike in the classical wavelet decomposition scheme it is possible to use different scaling and wavelet functions at every scale by using non-stationary multiresolution analyses. In this work we introduce parallel algorithms (suitable for MIMD architectures) that excel the execution speed for this type of lossy compression algorithms by far.

1 Introduction

Image compression methods that use wavelet transforms (which are based on multiresolution analysis (MRA)) have been successful in providing high rates of compression while maintaining good image quality (e.g. [4]). In the classical MRA scheme one uses a set of well chosen filtercoefficients to perform a convolution followed by a decimation from fine to coarse scales. Since all the transformations at each level are performed independently, it is possible to use different filtercoefficients at every scale. This theory of non-stationary MRA (NSMRA) was introduced in [2] – based on this there have been some papers published on exploiting the freedom in choosing different wavelet filters for different scale levels for adaptive image coding techniques (e.g. [5]).

When choosing such an adaptive technique, the execution times are far away from being real time - in this paper we introduce parallel algorithms (suitable for both shared and distributed memory MIMD architectures) that excel the execution time of the algorithms by far.

2 Non–stationary MRA decomposition and the best level filter selection algorithm

2.1 Non–stationary MRA decomposition

The classical 2-D wavelet decomposition is implemented by first convolving the rows of the low pass image S_{j+1} (or the original image in the first decomposition step) with the QMF filterpair G and H (which are a high pass and a low pass filter, respectively), retaining every other row, then convolving the columns of

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the resulting images with the same filterpair and retaining every other column. The same procedure is applied again to the coarse scale approximation S_j and to all subsequent approximations.

Since all the convolutions at different scale (or resolution) levels and image directions are performed independently we can define a generalized decomposition as follows:

A *NSMRA wavelet decomposition* is obtained by using different filterpairs for different scale levels of the decomposition (e.g. figure 1: filterpair G,H at scale level $j+1$, filterpair A,B at scale level j).

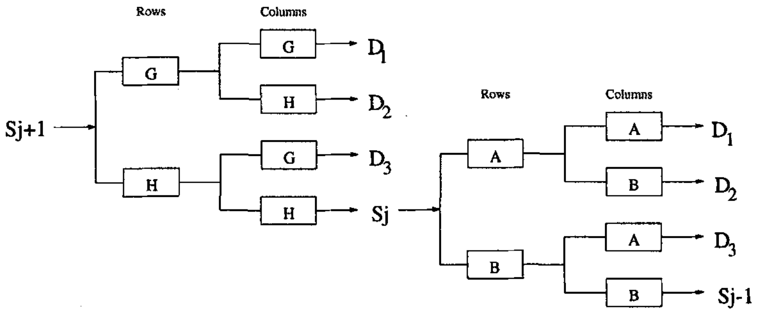

Fig. 1. 2-D NSMRA wavelet decomposition

2.2 Best level filter selection

Suppose we have given a filter–library containing l pairs of different wavelet filters and a fixed maximal decomposition depth m. It is possible to build with the filters contained in this library l^m different NSMRA wavelet decompositions (always including classical ones). Now we describe an algorithm that identifies good filtercombinations in this big set of possible ones in terms of a tree search problem.

Beginning at the top of the tree, we expand for the first scale level into l branches (corresponding to the decompositions using the l different filterpairs) and get l children nodes. Each of these nodes is expanded again for the second scale level into l branches leading to l^2 nodes at the second scale level. When the whole tree is expanded we arrive at l^m nodes at the bottom of the tree which correspond to l^m possible NSMRA decompositions using a library and decomposition depth of the given order.

Finding the best NSMRA decomposition in this tree corresponds to finding the node at the bottom level that gives the lowest information cost. A NSMRA decomposition is represented by a path from the root to a bottom node in the tree.

The best level filter selection algorithm can be described in terms of searching in this NSMRA decomposition tree as follows. After the decomposition of the first scale level using all the l filterpairs only the node with the lowest information cost (which is determined by evaluating an information cost function e.g. entropy [3] on the detail images) is expanded into its l branches (corresponding to the second scale level). The resulting l nodes are again evaluated and only the best one expanded. Following this procedure, only ml paths are investigated instead of l^m in a complete search.

In terms of classical tree search the best level filter selection algorithm is a hill-climb or a beam search expanding only the best node.

3 Parallel algorithms

There are basically two possibilities how to parallelize this algorithm:

1. **Parallelizing the wavelet transform:** this approach is a fine grained parallelization at which even SIMD architectures may be used for the calculation. Many papers have already been published on this topic.
2. **Parallelizing the tree search:** this is the more coarse grained approach which is treated in the next section.

3.1 Parallel best level filter selection

Depending on the type of architecture (massive or moderate parallel) and on the size of the chosen filterlibrary we have to distinguish between two situations concerning the relation between the number of processors and the number of filters – for these two situations different parallelization strategies have to be used:

a) #filters $\geq$ #processors
b) #filters $<$ #processors

Case a): Before the actual calculation takes place we assume that the filterlibrary and the image considered has already been broadcasted by the hostprogram to all nodeprograms.

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-) Each nodeprocessor is assigned one or more filters.
-) On each nodeprocessor one scale level decomposition with the
   assigned filters is done and the corresponding cost
   function is evaluated and sent to the hostprogram.
-) The hostprogram evaluates the best filter for this level.
-) The identified best decomposition is either broadcasted
   or recalculated using data-parallelism
-) Proceed to the next scale level
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Case b): The filters are assigned to the nodes according to some heuristics, nodes sharing the same filter partition their data and decompose independently. The hostprogram collects the costfunctions and determines the best filter.

3.2 Experimental Results

We have implemented the algorithm on a workstationcluster conisting of eight DEC AXP 3000/400 using PVM. According to the two cases introduced, we present speedup-results for filterlibraries consisting of 30 and 4 filters, respectively. Additionally we use different nodenumbers. Maximal decomposition depth for 512x512 images and entropy as cost- function is being used, the decomposition result of the best filter is broadcasted at each level.

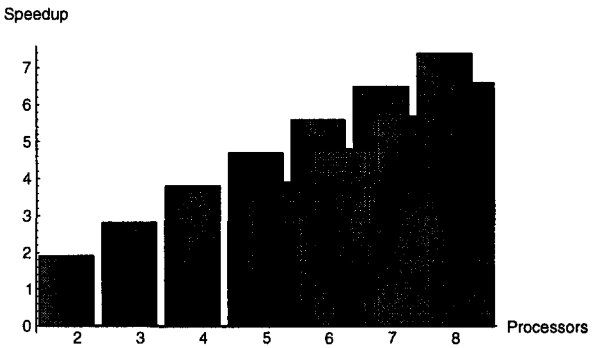

Fig. 2. Best level filter selection: speedup for case a) (2 - 8 nodes) and b) (5 - 8 nodes)

Good efficiency (close to linear speedup) is achieved when the number of filters in the library is a multiple (not necessarily integer) of the number of processors (due to less communication and synchronization demand of case a) – see figure 2). Generally the increase of the number of available processors reduces the efficiency (which is known as bad scalability in the literature) which implies that these algorithms should only be used on moderate parallel architectures. For parallelization on massive parallel machines we recommend the parallelization via the wavelet transform.

References

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