Computational Challenges in Processing Hyperspectral Images

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Motivation

Current status in remote sensing:

- Large hyperspectral images (containing hundreds of spectral bands) are available
- Need of tools to efficiently process large amount of data

Main challenges in processing large hyperspectral data:

- The image could be too large to be efficiently read and store on one computing node
- The image analysis could involve massive computations

Thus, an efficient exploitation of HPC particularities is required …

Aim of this work

To address the computational challenges of parallel implementations of two clustering algorithms for hyperspectral images :

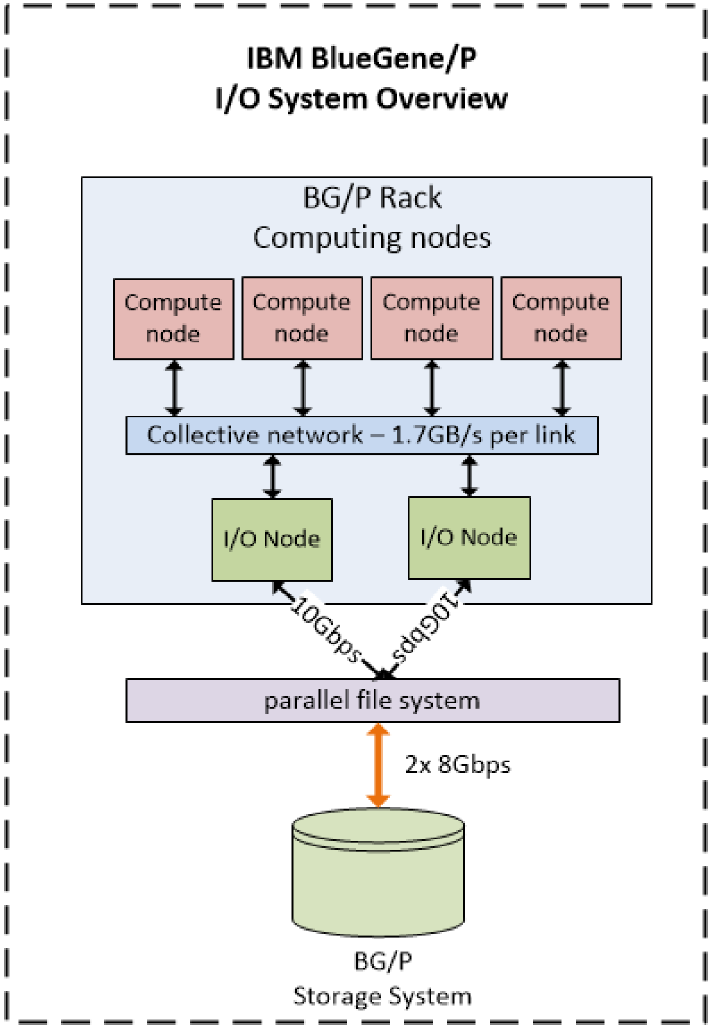
- a spatial variant of Fuzzy C-means (SFCM)
  - iterative process requiring collective computations and frequent transfer of data between computing nodes
- a morphological automated endmember extraction algorithm (AMEE)
  - requires the extraction of global endmembers from the local ones generated at each computing node and the computation of a similarity measure between a large number of endmembers

in the context of using

- BlueGene/P supercomputer
- 1024 quad-core, 850Mhz PowerPC 450d each with 1GB RAM

I/O challenges

- When reading and storing large amount of data on BlueGene/P one should take BG/P I/O System particularities



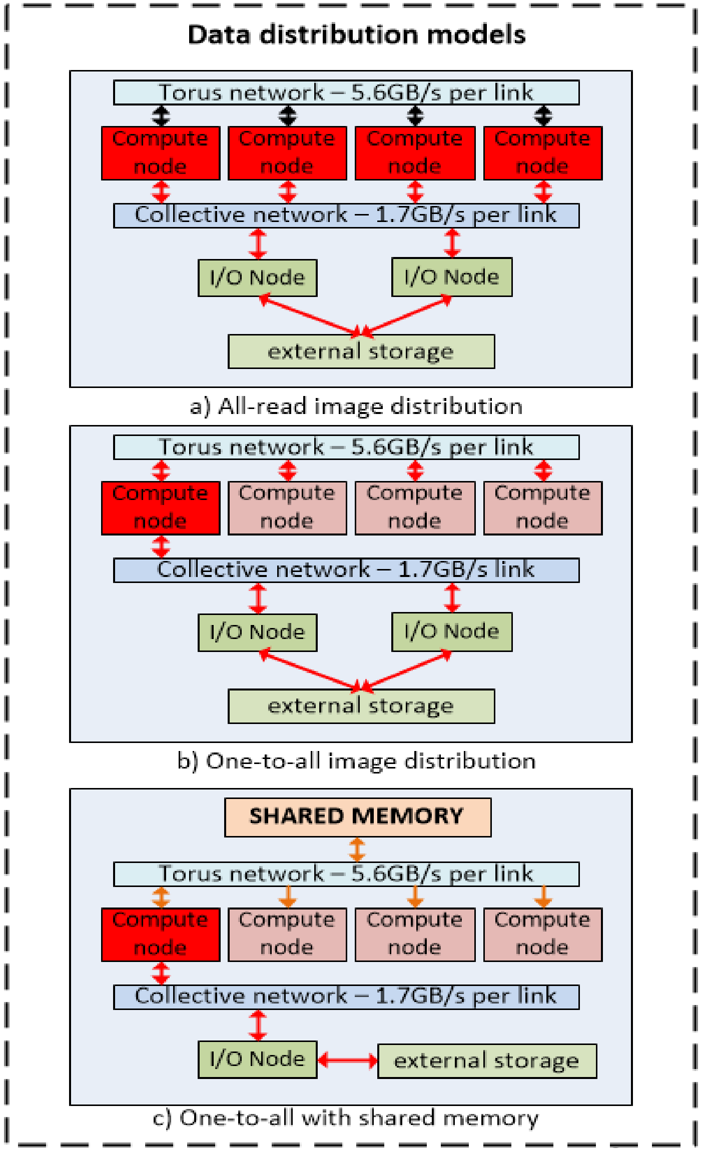
I/O challenges

Possible approaches:

a) All-read image distribution

b) One -to-All image distribution

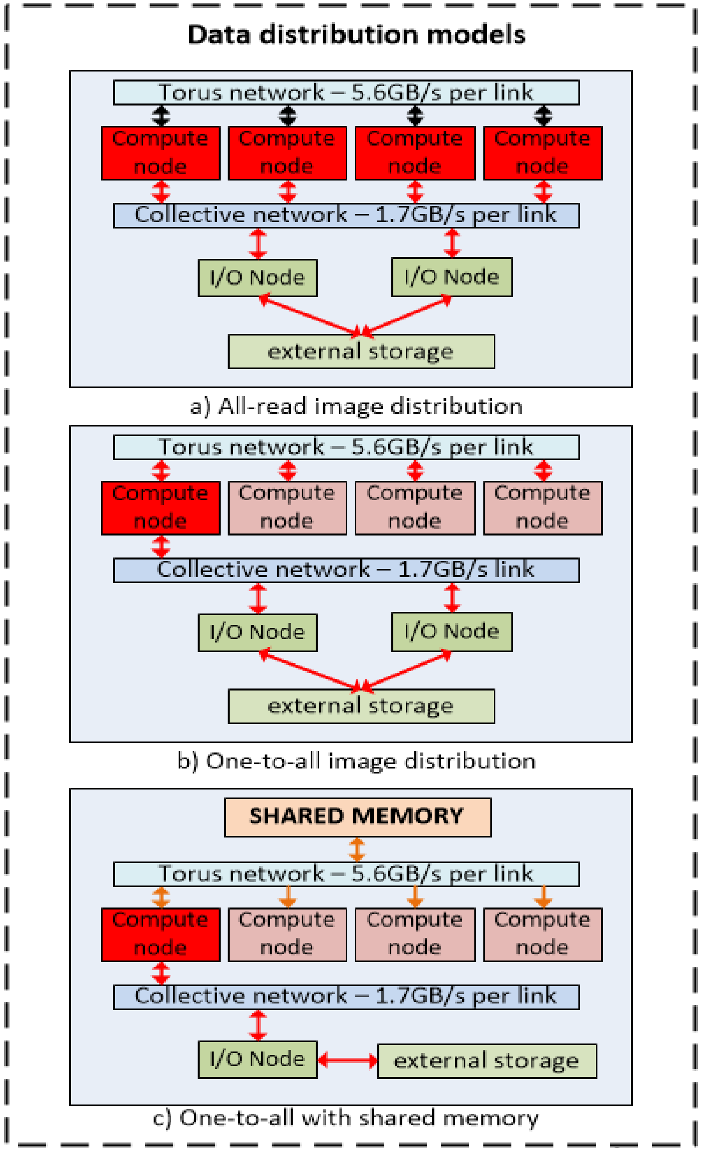
c) One-to- All using shared memory



I/O challenges

All-read image distribution

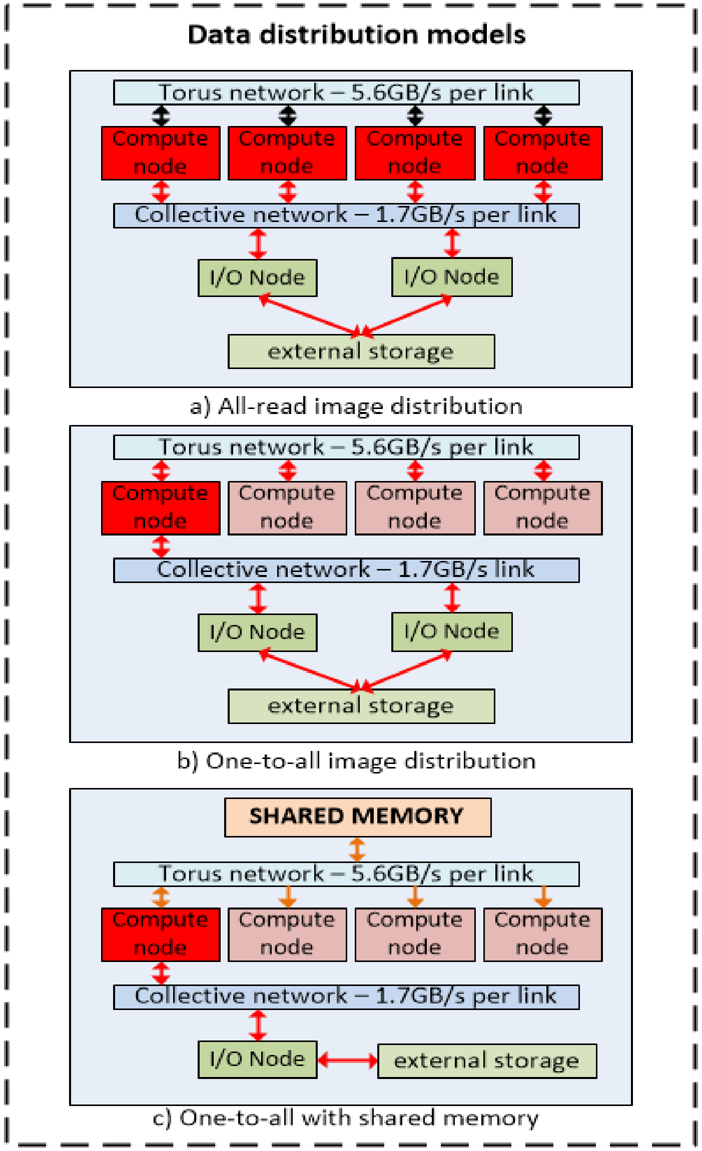
- Simplest but less efficient
- Memory usage :
  - each processor has to load the entire image into memory and extract only one slice of it
- Network bandwidth usage:
  - each processor the entire image into memory -> the network bandwidth becomes soon inefficient



I/O challenges

One-to-all image distribution

- Minimizes the storage-memory data load
- Main particularities:
  - a subset of computing nodes are selected to be data distribution processors
  - the image slices are distributed over the computing nodes via the MPI communication subsystem
  - the number of data distribution nodes should be carefully selected in order to not induce high communication overhead

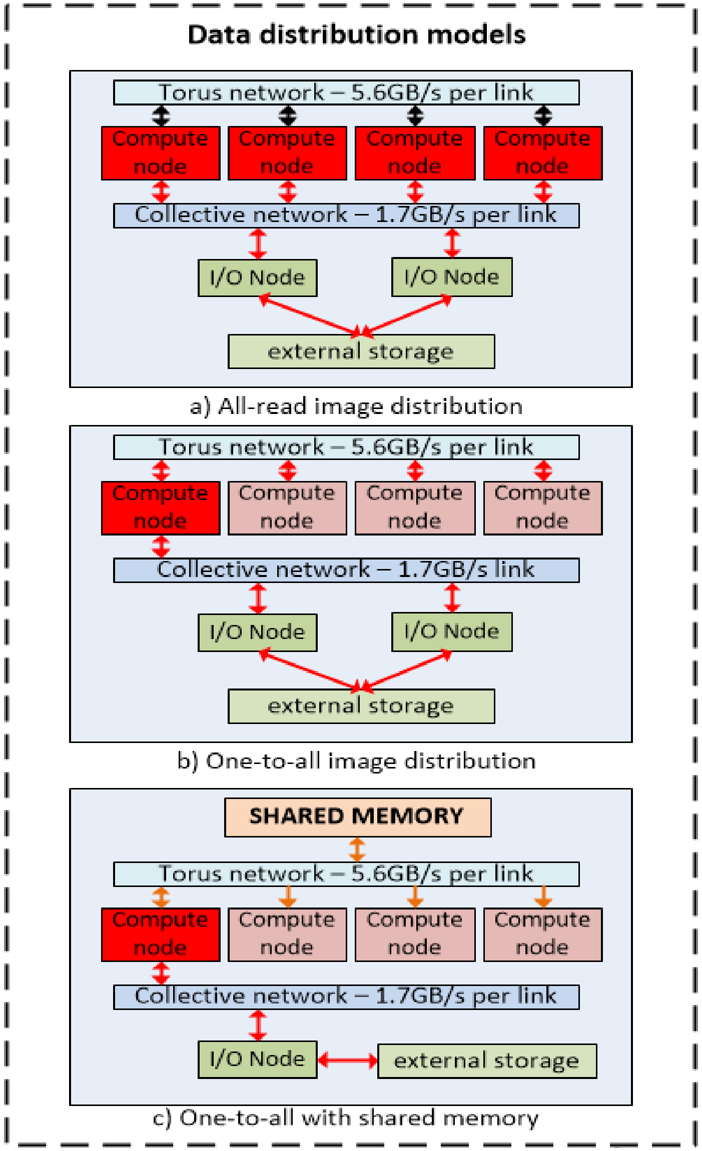


I/O challenges

One-to-all using shared memory

- Optimized version of one to all image distribution model

- Main particularities:
  - usage of global arrays toolkit for exposing a shared image such that the computing nodes can copy their corresponding slices
  - one processor read the image and populate a data structure in a shared memory



Computational Challenges

- **Case study** for parallel unsupervised classification (clustering) based on two iterative algorithms: SFCM and AMEE
- **Input data:**
  - Image = $\{x_1, \ldots, x_n\}$, n = number of pixels, $x_i = (x_{i1},\ldots, x_{id})$, d = number of spectral bands

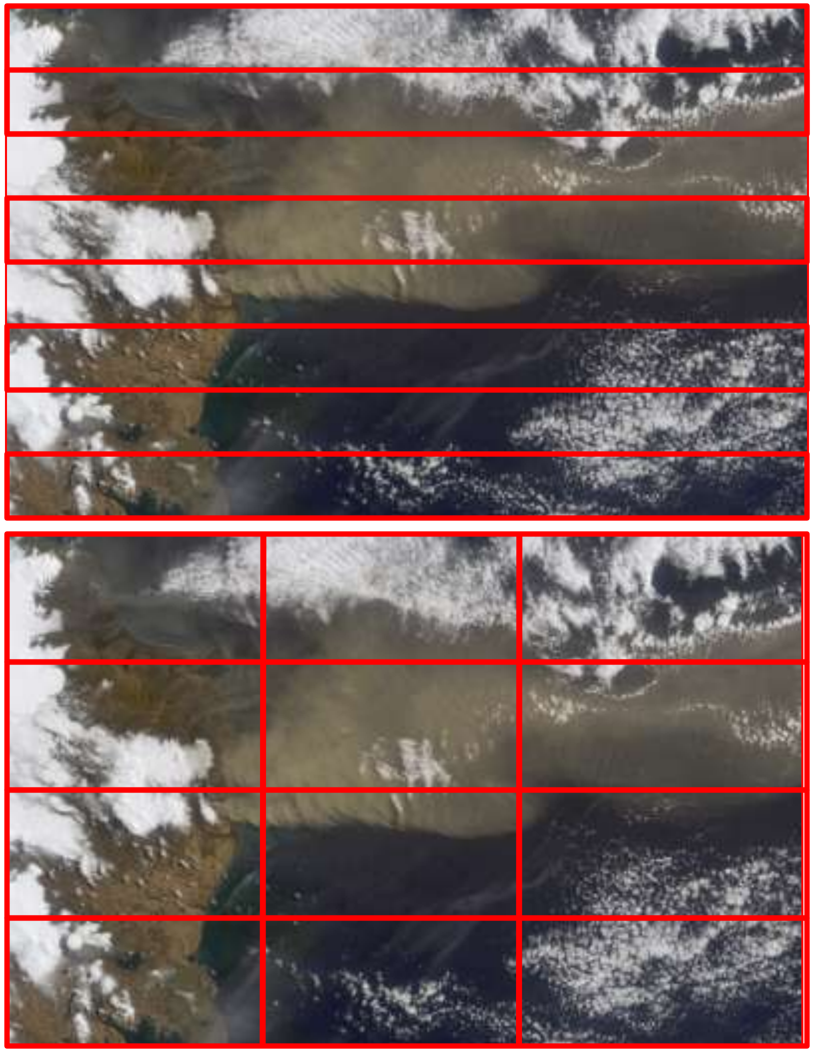
    (set of vectors corresponding to all pixels and containing the values corresponding to the spectral bands)
  - Number of classes/ endmembers to be identified (c)
- **Output data:**

  SFCM: membership matrix (of size c x n): u_{ij} is a value in [0,1] specifying the degree of membership of pixel i to class j; classes centroids = $\{v_1,\ldots,v_c\}$

  AMEE: set of endmembers (of size c x n)
  - Classified image = $\{y_1,\ldots,y_n\}$, y_i = value related to the label of the class to which x_i belongs

Parallelization Idea

- **Split the image in slices**
  - horizontal/vertical slices
  - rectangular slices
- **Process each slice and compute local info**
  - SFCM: local membership values
  - AMEE: local endmembers
- **Collect/transfer local information via**
  - collective operations (MPI AllReduce)
  - point to point transfer (MPI Send/Recv)



Spatial Fuzzy C-Means

SFCM Algorithm [Chuang, 2006]

- Initialization of the membership values
- DO
  - Compute the centroids
  - Compute the spatial information (h_{ij})
  - Estimate the membership values (u_{ij})
  - Adjust the membership values (u_{ij})
  - WHILE (there are significant changes in the membership values)
- Construct the classification

Centroids computation (global)

$$v_j = \frac{\sum_{i=1}^{n} u_{ij}^m x_i}{\sum_{i=1}^{n} u_{ij}^m}, \quad j = \overline{1, c}$$

m>1 is a parameter (e.g. m=2)

Membership values estimation (local)

$$w_{ij} = \frac{1}{\left\| x_i - v_j \right\|^{2/(m-1)} \sum_{k=1}^{c} 1 / \left\| x_i - v_k \right\|^{2/(m-1)}}$$

$$\boxed{u_{ij} = \frac{w_{ij}^p h_{ij}^q}{\sum_k w_{ik}^p h_{ik}^q}, \quad h_{ij} = \sum_{k \in N(i)} w_{kj}}$$

$$i = \overline{1, n}, \; j = \overline{1, c}$$

Parallel SFCM

- **Split the image in slices:** $S_1, \ldots, S_P$
- **Split the computation:**

$$v_j = \frac{\sum_{i \in S_1} u_{ij}^m x_i + \ldots + \sum_{i \in S_P} u_{ij}^m x_i}{\sum_{i \in S_1} u_{ij}^m + \ldots + \sum_{i \in S_P} u_{ij}^m}$$

- **Processor k computes:**
  - The corresponding membership values (requires transfer of border values between processors dealing with neighboring slices)
  - The partial sums involved in the centroids computation

$$\sum_{i \in S_k} u_{ij}^m x_i \quad \text{and} \quad \sum_{i \in S_k} u_{ij}^m$$

  - The local maximal difference between the membership values at two consecutive iterations

$$\max\{|u_{ij}(\text{iter}+1) - u_{ij}(\text{iter})|;\ i \in S_k,\ j = \overline{1,c}\}$$

Parallel AMEE

Algorithm 1 AMEE Parallel

Scatter N partial data structures $\{PSSP\}_{n=1}^{N}$ of F
$i = 1$
$MEI(x, y) = 0, \forall (x, y) \in PSSP_n$
while $i < I_{max}$ **do**
  Move kernel through each pixel
  Compute minimum and maximum
  Update MEI with SAM between minimum and maximum
  $i = i + 1$
  if $i == I_{max}$ **then**
    break
  else
    Replace $PSSP_n$ with its dilation
  end if
end while
Select P endmembers with highest MEI scores
Master gathers all endmembers and forms a unique set of P endmembers by computing all possible pairs

Notations:

PSSP = image slice

MEI = matrix of eccentricity indices

kernel = structuring element for the morphological operation

SAM = spectral angle measure

P= number of endmembers

Experiments: Implementation

BlueGene/ P

- Nodes: 32 nodes x 32 compute cards x 1CPU
- CPU: 850Mhz PowerPC 450d, 4 cores per CPU (32 bits mode);
- RAM: 1GB / core;
- High-speed interconnect: 3D Torus 40Gbps bandwith (3µs response time on MPI communication)
- Collective interconnect: 53Gbps bandwith (5µs response time for MPI communication)

Parallel implementation:

C, MPI (MPICH-2), libtiff (3.9.1)

Communication between processors:

MPI_COMM_WORLD

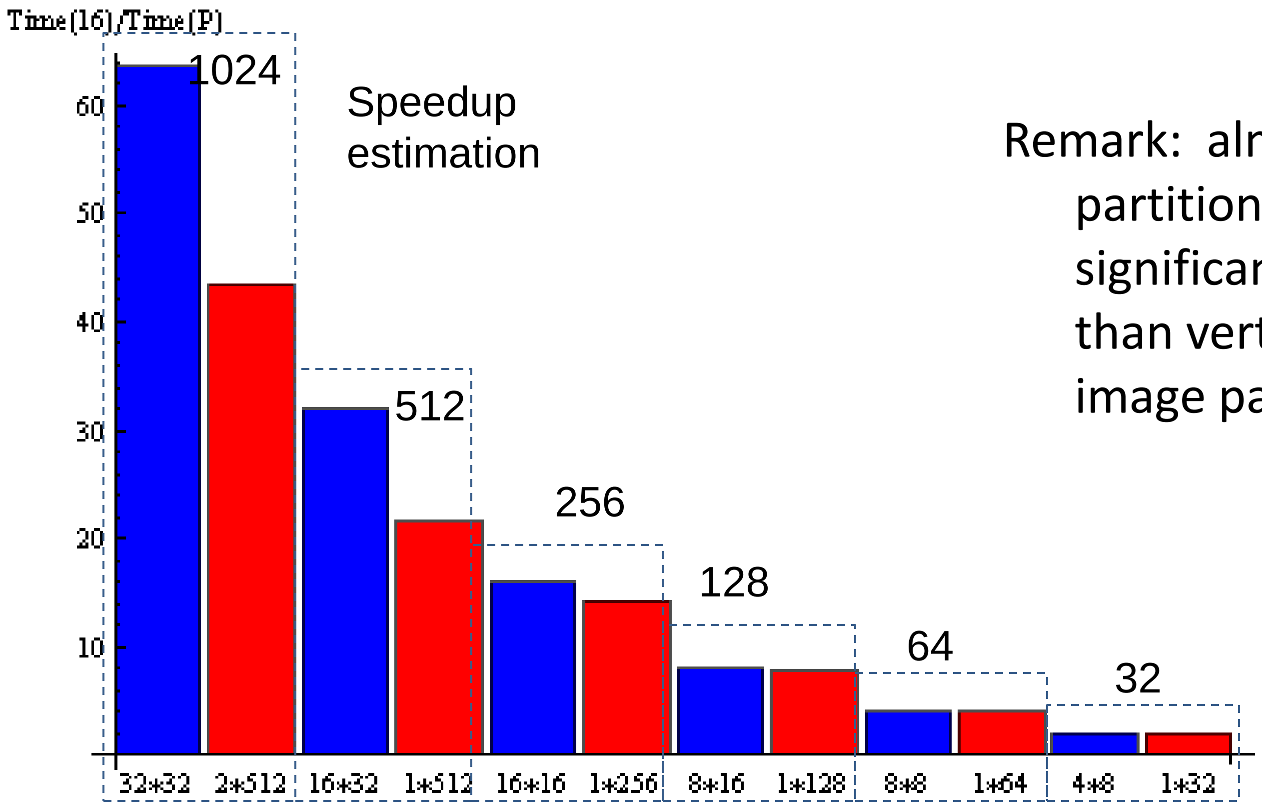
MPI_AllReduce

MPI_Send, MPI_Recv (SFCM)

Particularities:

- IBM XL Compiler
- MPICH BlueGene/P version
- optimization flags: "-O3 -qhot -qipa=level=2 -qarch=450d".

SFCM: influence of partitioning



Remark: almost square like partitioning leads to a significantly better speedup than vertical (or horizontal) image partitioning

Test image: AVIRIS Low Altitude (224 bands, 614x1097 pixels)
http://aviris.jpl.nasa.gov/html/aviris.freedata.html

Algorithm:SFCM

Parameters: 100 iterations, 5 classes, neighborhood size=5

AMEE: optimization

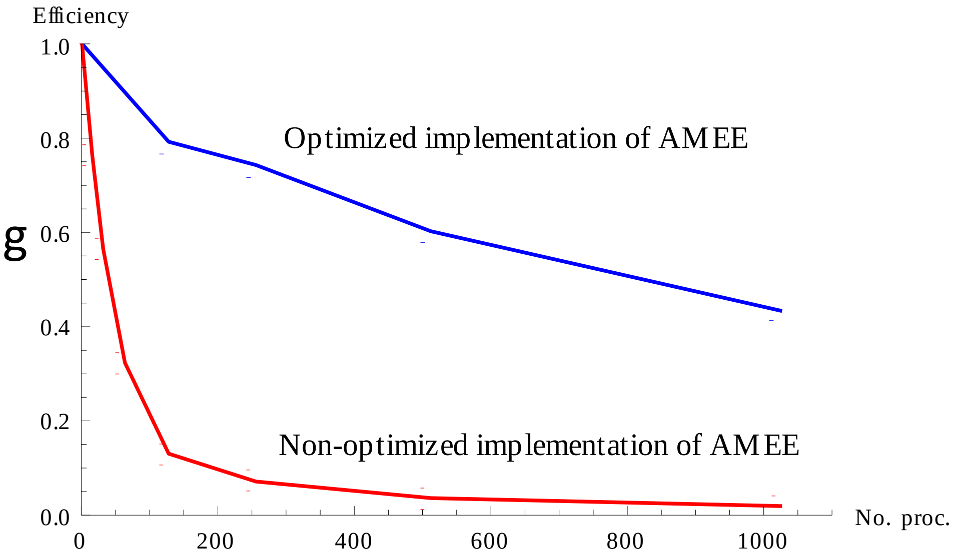
Optimization elements:

$$s(e_i) = \sum_{j=1}^{P \cdot E} \left(\left(\sum_{k=1}^{B} e_i^k \cdot e_j^k\right) / \left(\|e_i\| \cdot \|e_j\|\right) \right)$$

$$\Downarrow$$

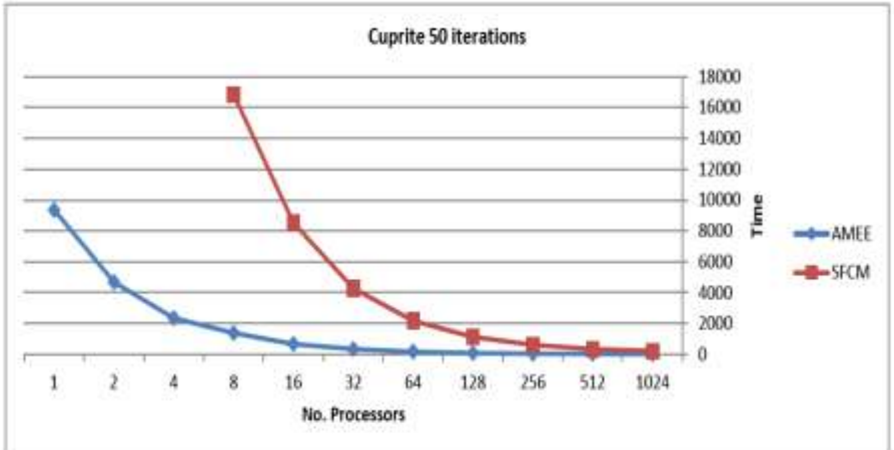
$$s(e_i) = \frac{1}{\|e_i\|} \sum_{k=1}^{B} e_i^k \sum_{j=1}^{P \cdot E} \frac{e_j^k}{\|e_j\|}$$

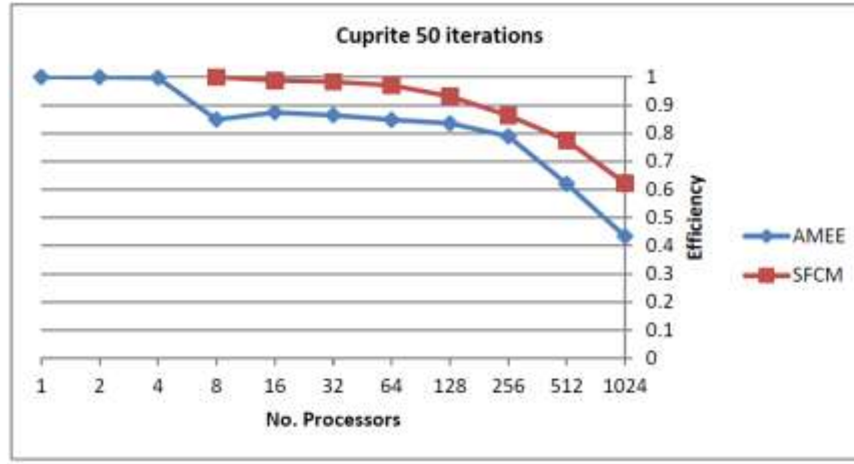
- exploit the structure of spectral angle metric to optimize the paired distances between local endmembers
- avoid a global computation by a particular procedure to merge local sets of endmembers
- control the synchronization among processes in the context of using collective communications (MPIBarrier)



Test image: AVIRIS Cuprite (224 bands, 614x2206 pixels)

Comparative results





Test image: AVIRIS Cuprite (224 bands, 614x2206 pixels)

Remarks:

- computational costs of SFCM higher than for AMEE
- better efficiency for parallel SFCM than for parallel AMEE

Comparative results

Test image: AVIRIS Cuprite (224 bands, 614x2206 pixels)

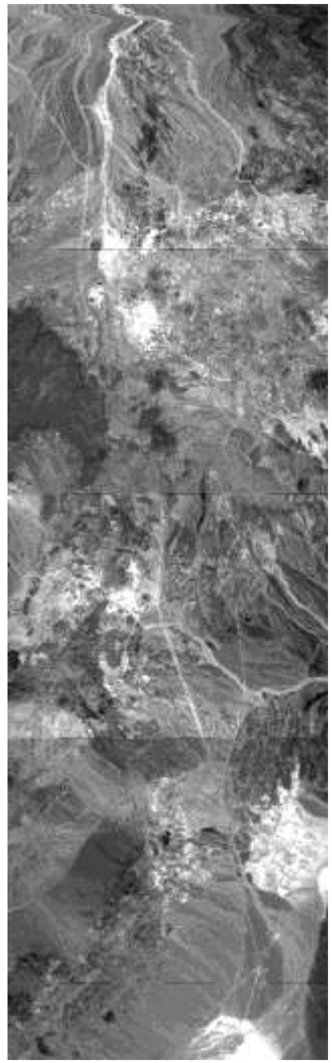
Left: original image

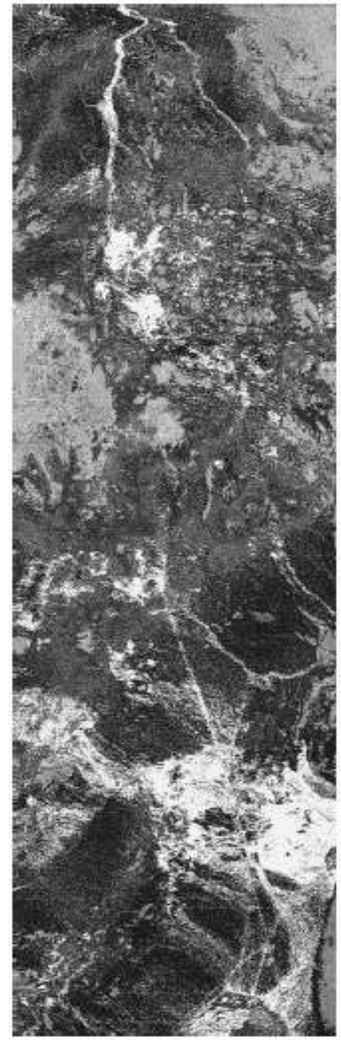
Middle & right: results after 50 iterations

Clustering quality index:

(V_K = Kwon index)

- smaller values mean better clustering
- SFCM leads to a better clustering





(a) AMEE, $V_K = 51.9$

(b) SFCM, $V_K = 13.04$

Conclusions

Efficient parallel implementations hyperspectral images processing algorithms requires:

- exploitation of I/O system particularities
- careful division of the image in order to minimize the point to point communication costs
- optimized usage of collective operations

Choosing an appropriate classification algorithm usually leads to:

- trade-off between costs and the classification quality