LLNL-PRES-670952

Exploration of Lossy Compression for Application-level Checkpoint/Restart

Naoto Sasaki[1], Kento Sato[3],

Toshio Endo[1,2], Satoshi Matsuoka[1,2]

[1] Tokyo institute of technology

[2] Global Scientific Information and Computing Center

[3] Lawrence Livermore National Laboratory

Needs for Fault Tolerance

The scale of HPC systems are exponentially growing

- exa-scale supercomputers in about 2020
- The failure rate increases as systems size grows

Applications' users want to continue its computation even on a failure

Checkpoint/Restart technique is widely used as fault tolerant function

- But this technique has problems

Needs for Reduction in Checkpoint Time

Checkpoint/Restart

→Data of memory is stored in the disk

→High I/O cost

On TSUBAME2.5
Memory capacity : about 116TB
I/O throughput : about 8GB/s
↓
Checkpoint time : about 4 hours

MTBF(Mean Time Between Failure) is reduced by expansion in the scale of HPC systems

- MTBF is projected to shrink to over 30min in 2020 [※1]

If MTBF < Checkpoint time
an application may not be able to run !
↓
Needs for reduction in checkpoint time !

Applications' users need to reduce checkpoint time

※1 : Peter Kogge, Editor & Study Lead (2008)
ExaScale Computing Study: Technology Challenges in Achieving ExaScale Systems

To Reduce Checkpoint Time

There are techniques to reduce checkpoint size

- Compression
- Incremental checkpointing
    - This stores only differences with the last checkpoint

Compression can be combined with incremental checkpointing

- In addition, the effect of incremental checkpointing may be limited in scientific applications

We focus on compression for checkpoint image data

Lossless and Lossy Compression

gzip, bzip2, etc.

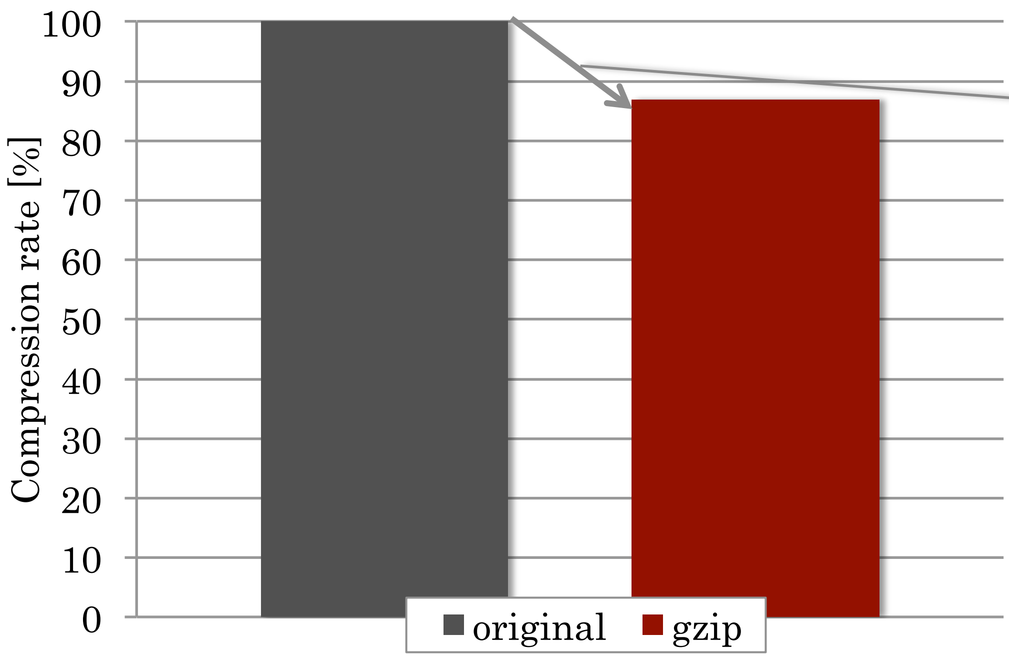
Features of lossless

- No data loss
- Low compression rate without bias
  - Scientific data has a randomness

jpeg, mp4, etc.

Features of lossy

- High compression rate
- Errors are introduced



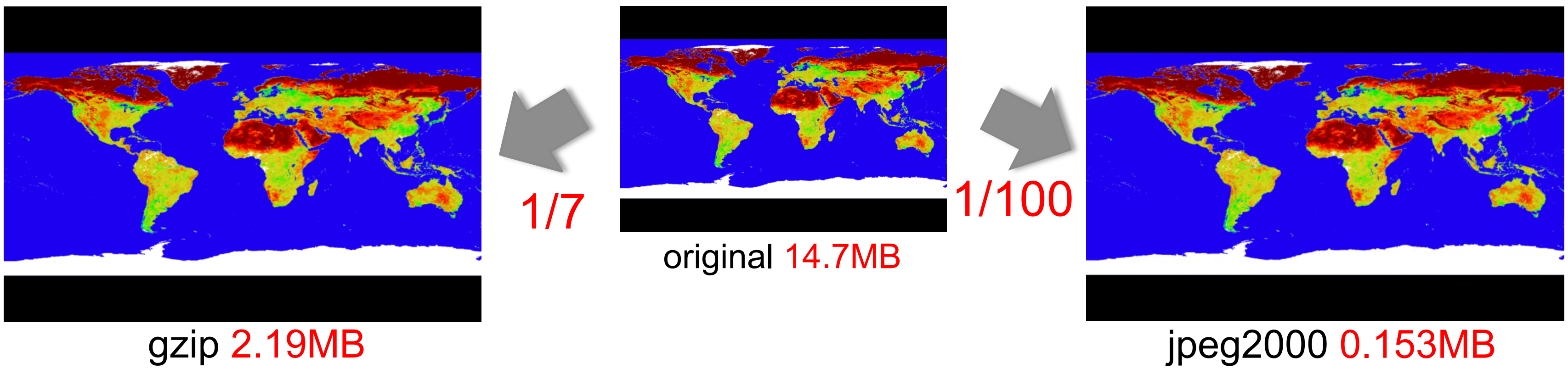
If we apply lossless compression to floating point arrays, the compression rate is limited

We focus on lossy compression

Discussion on Errors Introduced by Lossy Methods

Errors may be acceptable if we examine processes for developing real scientific applications

- Scientific model and sensors also introduce errors
- We need to investigate whether the errors are acceptable



(citation of images : http://svs.gsfc.nasa.gov/vis/a000000/a002400/a002478/)

Don’t apply lossy compression to data that must not have an error (e.g. pointer)

We apply lossy compression to checkpoint data

- The calculation continues with data including errors

Outline of Our Study

Purpose

- To reduce checkpoint time, lossy compression is applied to checkpoint data then checkpoint size is reduced

Proposed Approach

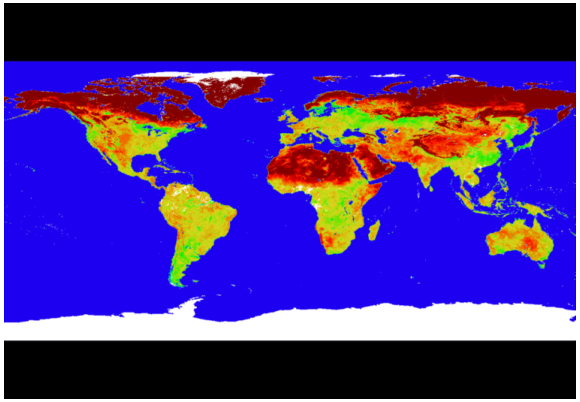
1. We apply wavelet transformation, quantization and encoding to a target data, then store the data in a recoverable format
2. We apply *gzip* to the recoverable format data

Contribution

- We apply our approach to real climate application, NICAM, then overall checkpoint time included compression time is reduced by 81% with 1.2% relative error on average in particular situation

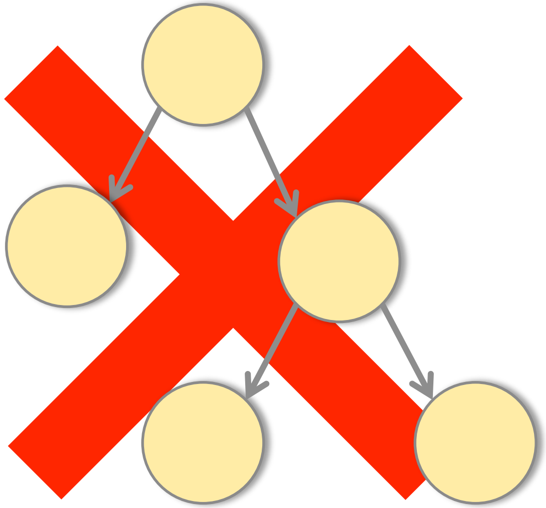
Assumption for Our Approach

We assume application−level checkpoint



- We utilize that difference between neighbor values
- Target data are an arrays of physical quantities
    - We target 1,2 or 3D mesh data represented by floating point arrays

There are data to which must not be applied our approach because errors are introduced



- Data structure including pointers (e.g. tree)

Users specify a range of data to which are applied our approach

Motivation of Wavelet Transformation

Lossless compression is effective in data that have redundancy

- Scientific data has a randomness
- We need to make redundancy in the scientific data

To make much redundancy and make errors small…

- The target data should have dense and small values

The scientific data does not spatially changed much

To make good use of this feature…

We focus on wavelet transformation

About Wavelet Transformation

Wavelet transformation is a technique of frequency analysis

Haar

We suspect that compression that uses wavelet transformation is efficient in applications that uses physical quantities (e.g. pressure, temperature)

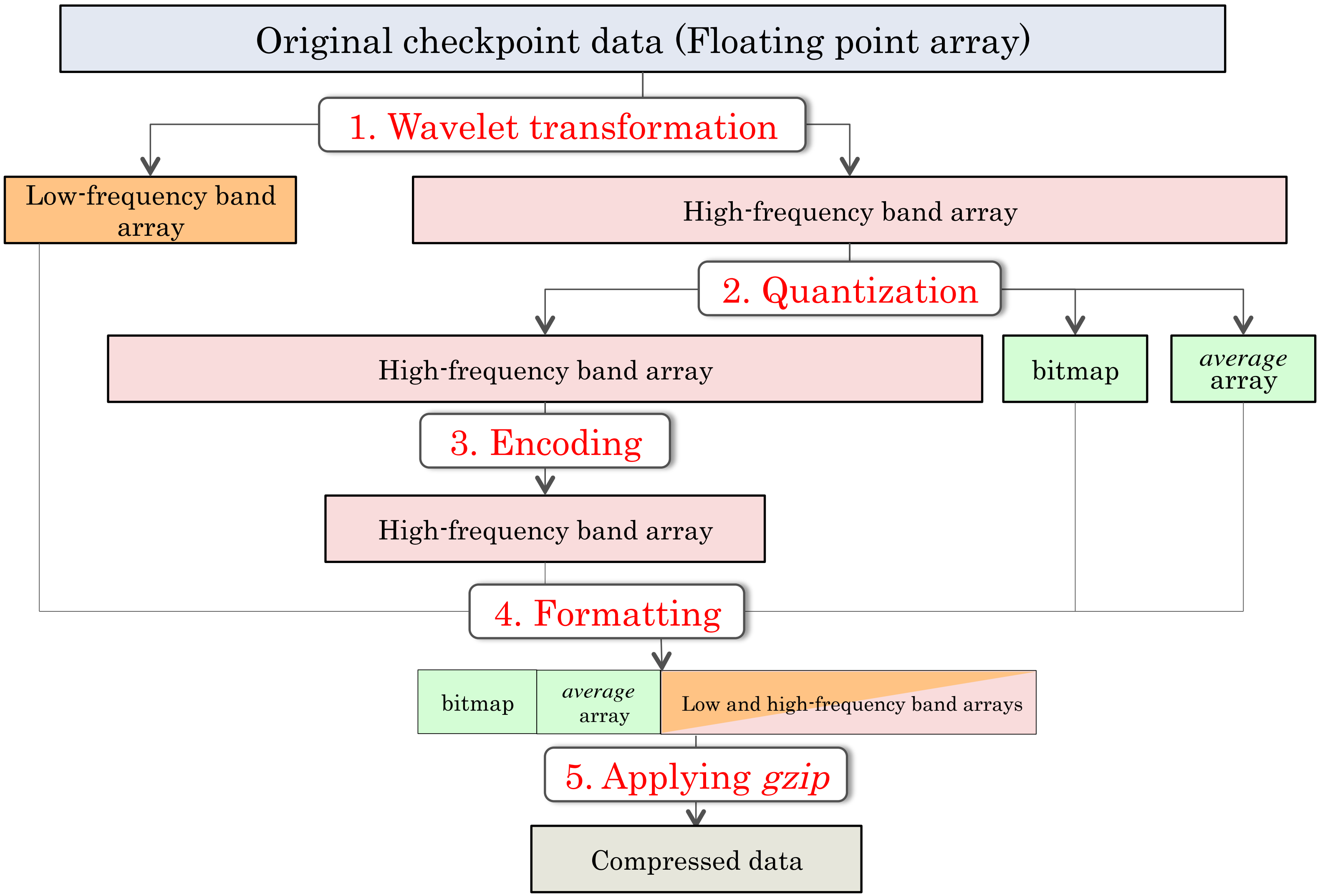
/dwavelet/DWTTut.html

Multiple resolution analysis is effective in compression

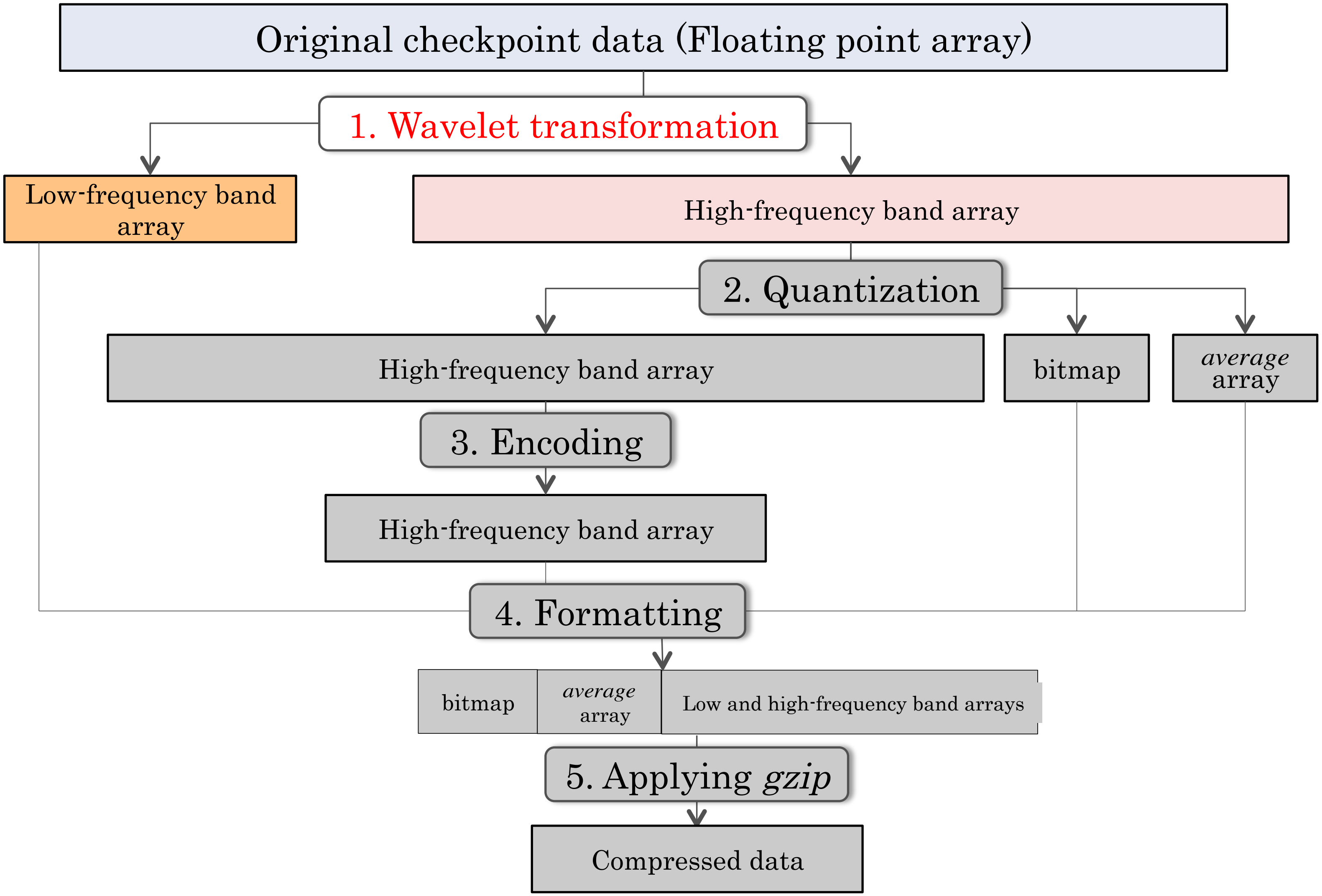
- JPEG2000 uses this technique
- It is known that this technique is effective in *smooth* data
  - This "*smooth*" means the difference between neighbor values is small

※Wavelet transformation itself is NOT compression method, but we use it for preprocessing

Proposal Approach: Lossy Compression Based On Wavelet



Wavelet Transformation



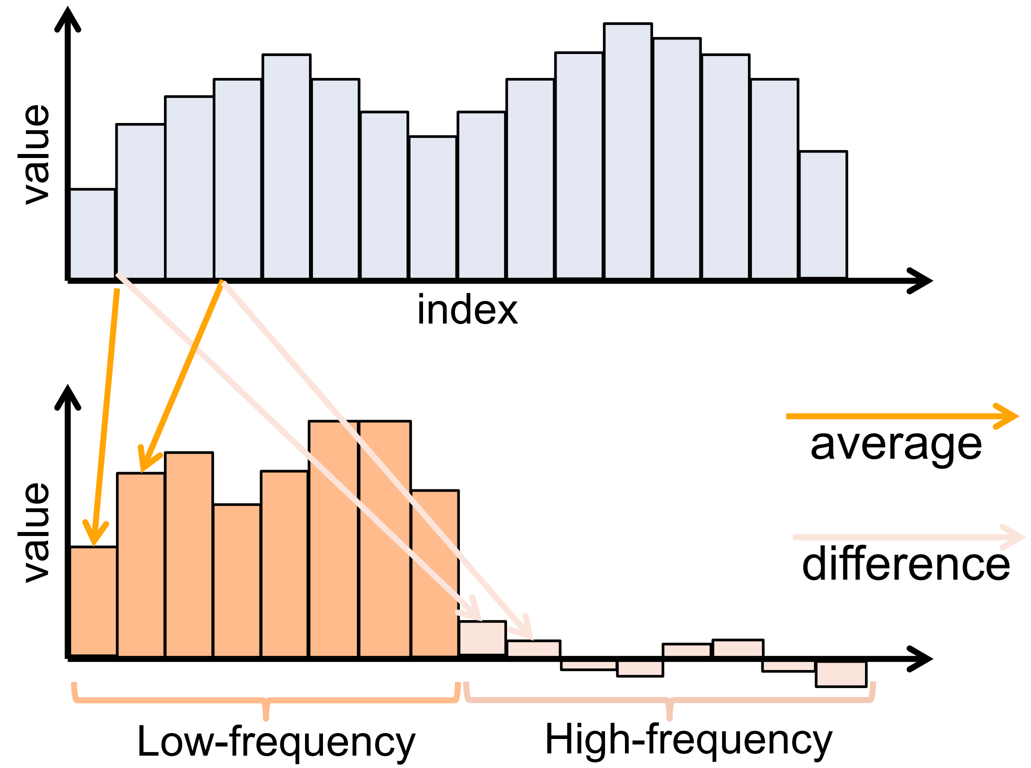
1D Wavelet Transformation in Our Approach

We use average of two neighbor values and difference between two neighbor values

Original 1D array

Wavelet transformation

Transformed array



In high-frequency band, most of values are close to zero

→We expect that an introduced error is small even if the precision of values in high-frequency band region is dropped

Multi-dimensional Wavelet Transformation

In multi-dimensional array, we apply 1D wavelet transformation to each dimension

In case of 2D array

- # of low…1
- # of high…3

In case of 3D array

- # of low…1
- # of high…7

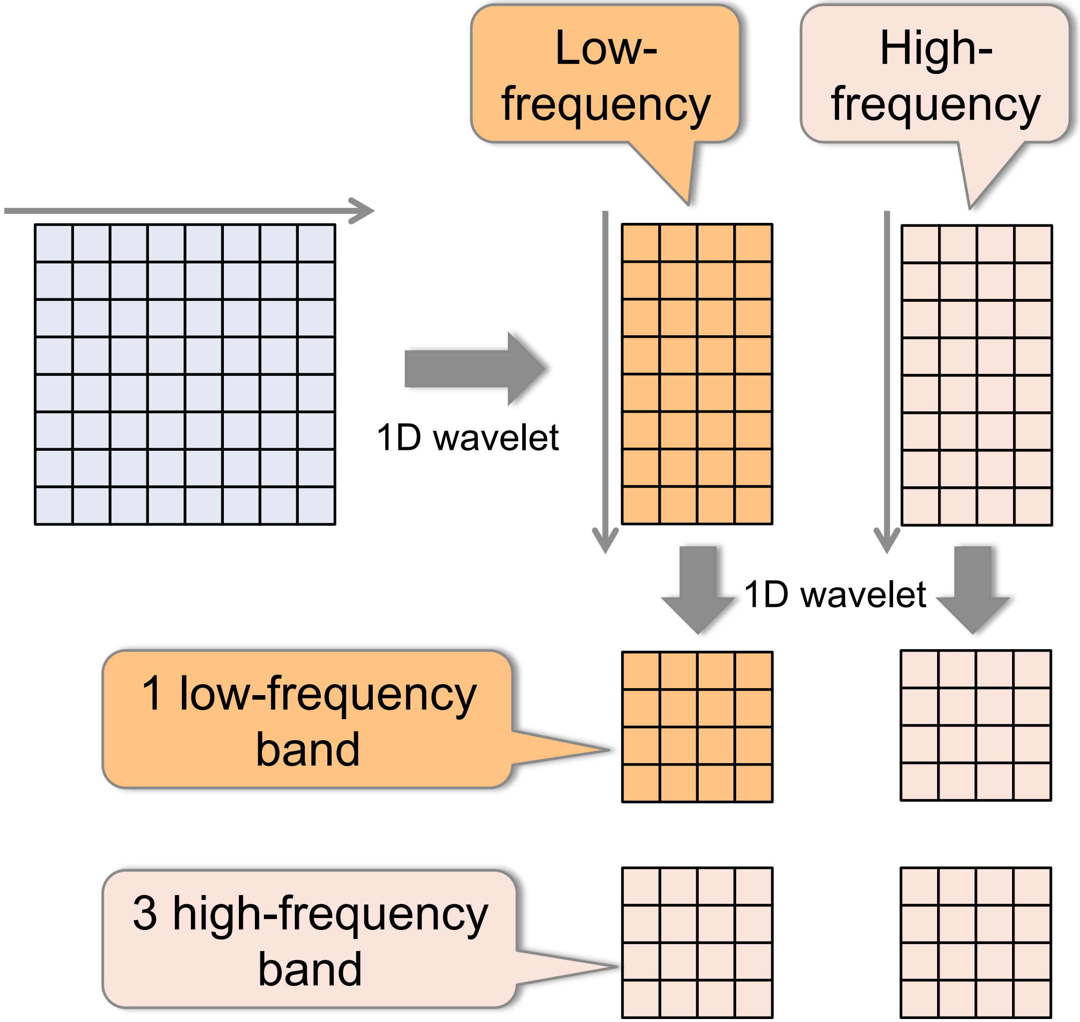
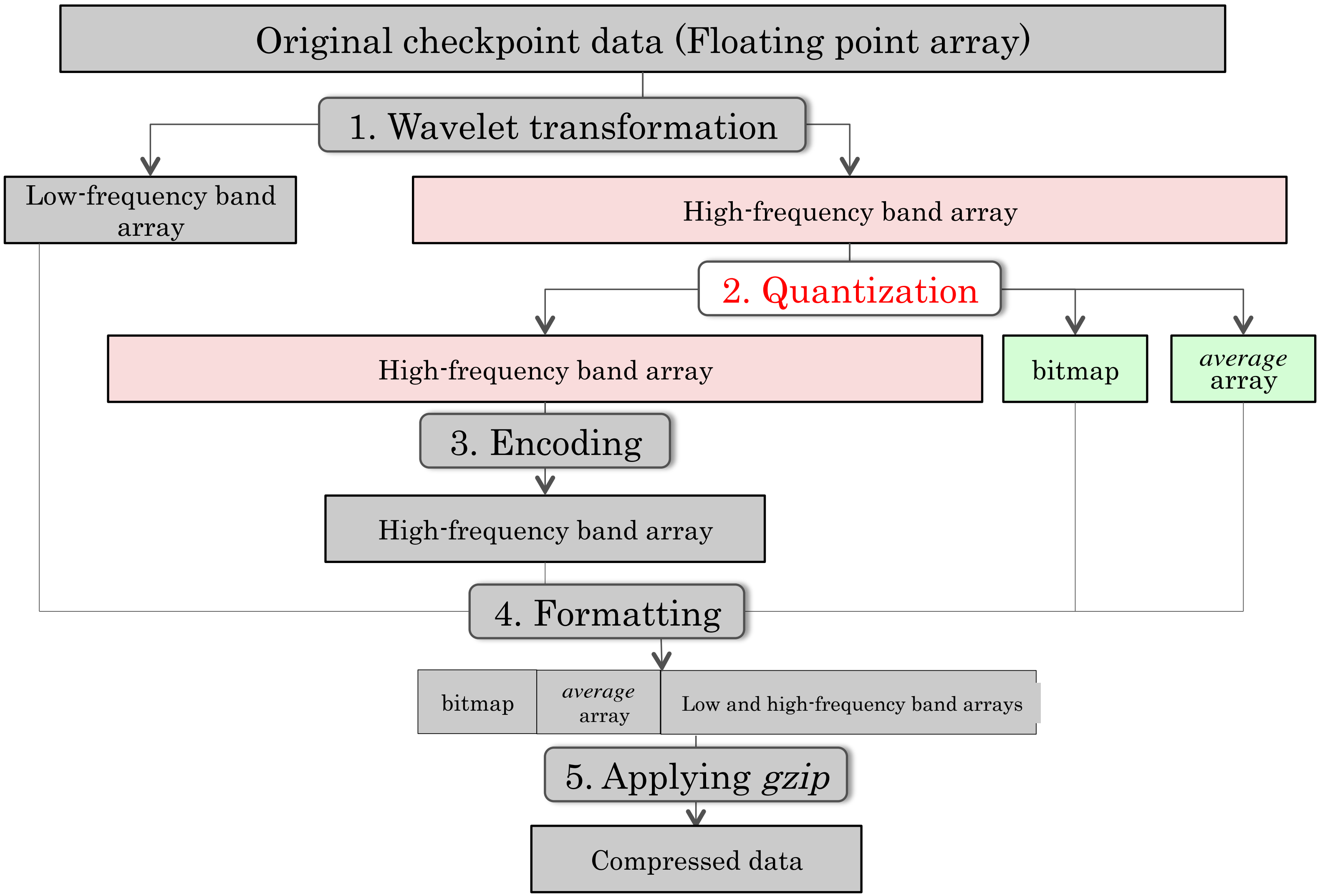


Fig : an example of wavelet transformation for a 2D array

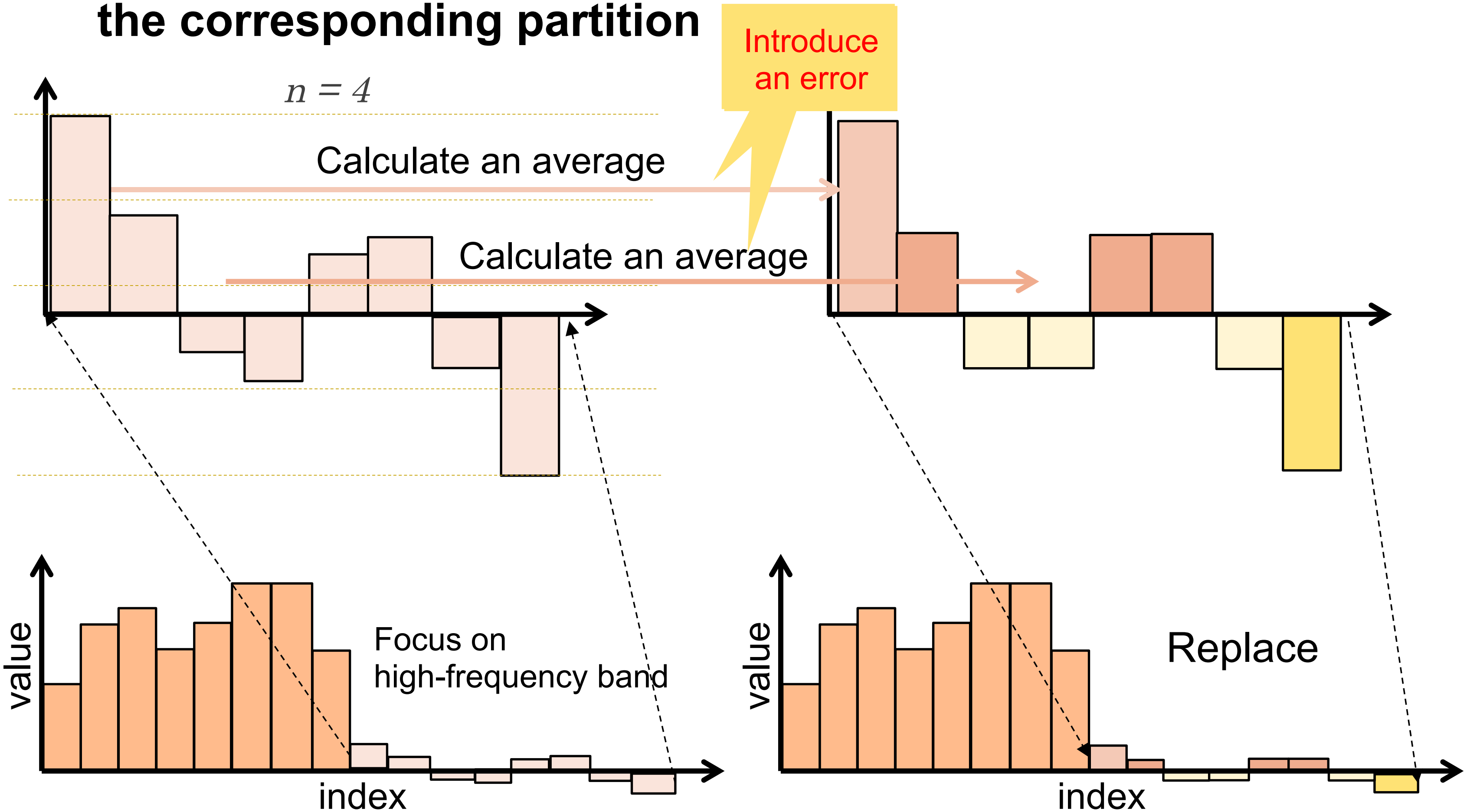
Quantization



Simple Quantization

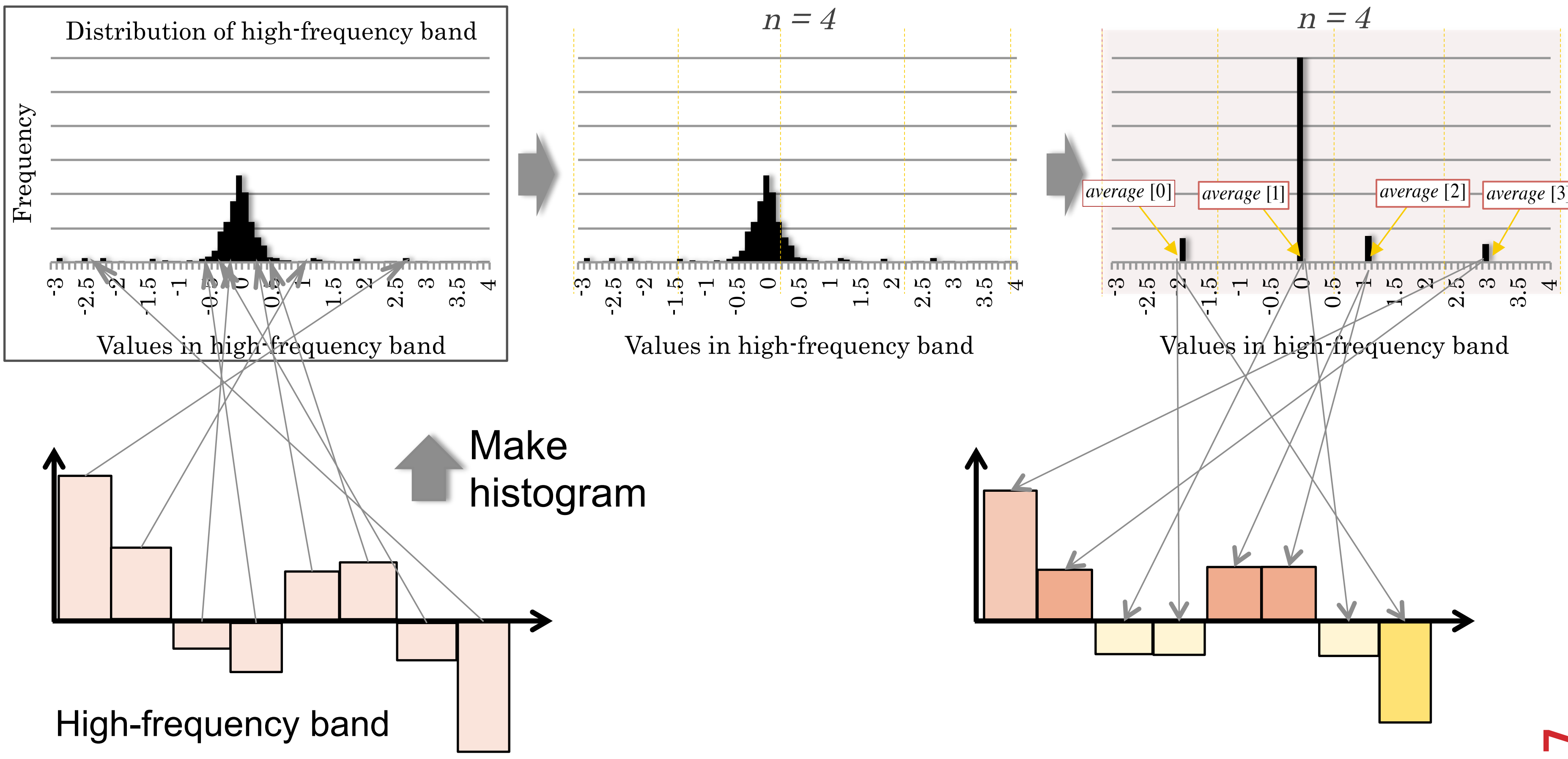
1. **Divide high-frequency band values into *n* partitions**
   - This *n* is called the number of division
2. **Replace all values of each partition with an average of the corresponding partition**

Introduce an error



Problems of Simple Quantization

Simple quantization introduces large errors



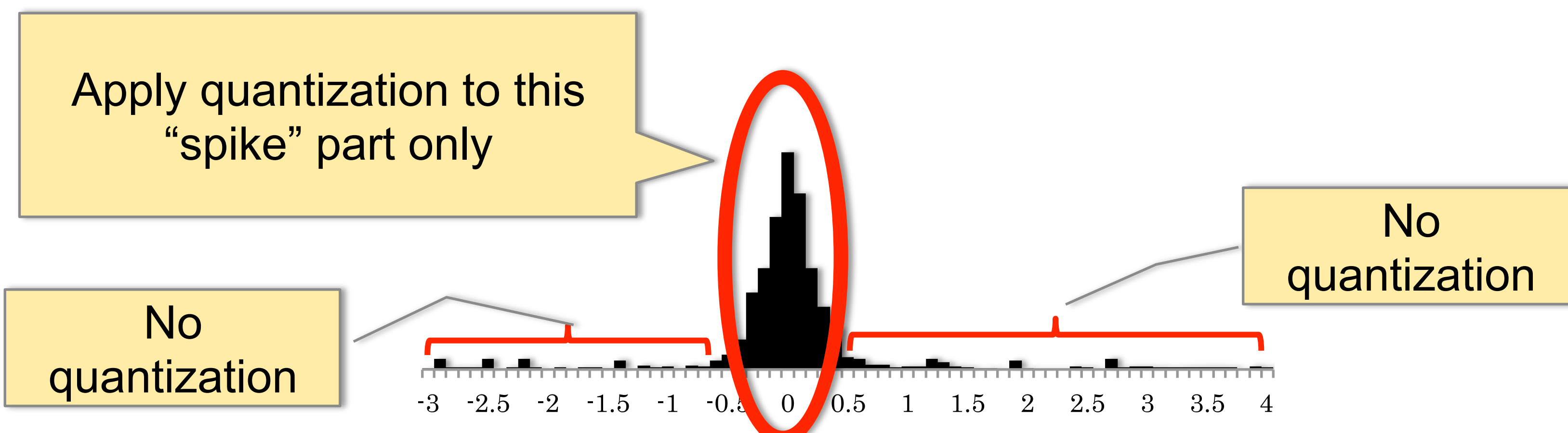
To reduce Errors

Target data is expected to be smooth

- Most of values in high-frequency band are close to zero
    - These make a "*spike*" in the distribution

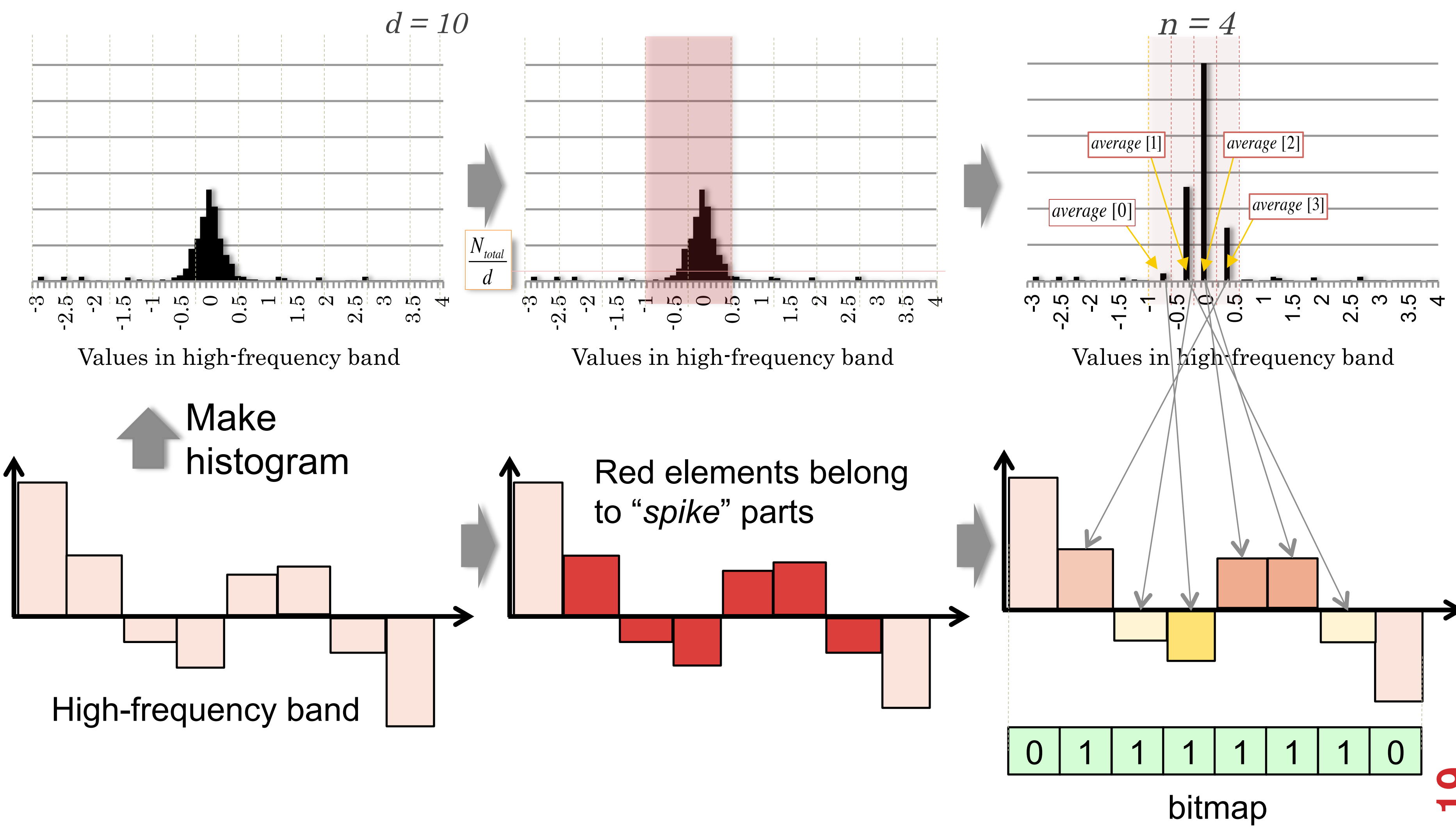
To reduce an error, we apply the quantization to the "*spike*" parts only

- An impact on compression rate is low because the spike parts consist of most of values in high-frequency band



Proposed Quantization

This method is improved version of simple one



Difference in quantization methods

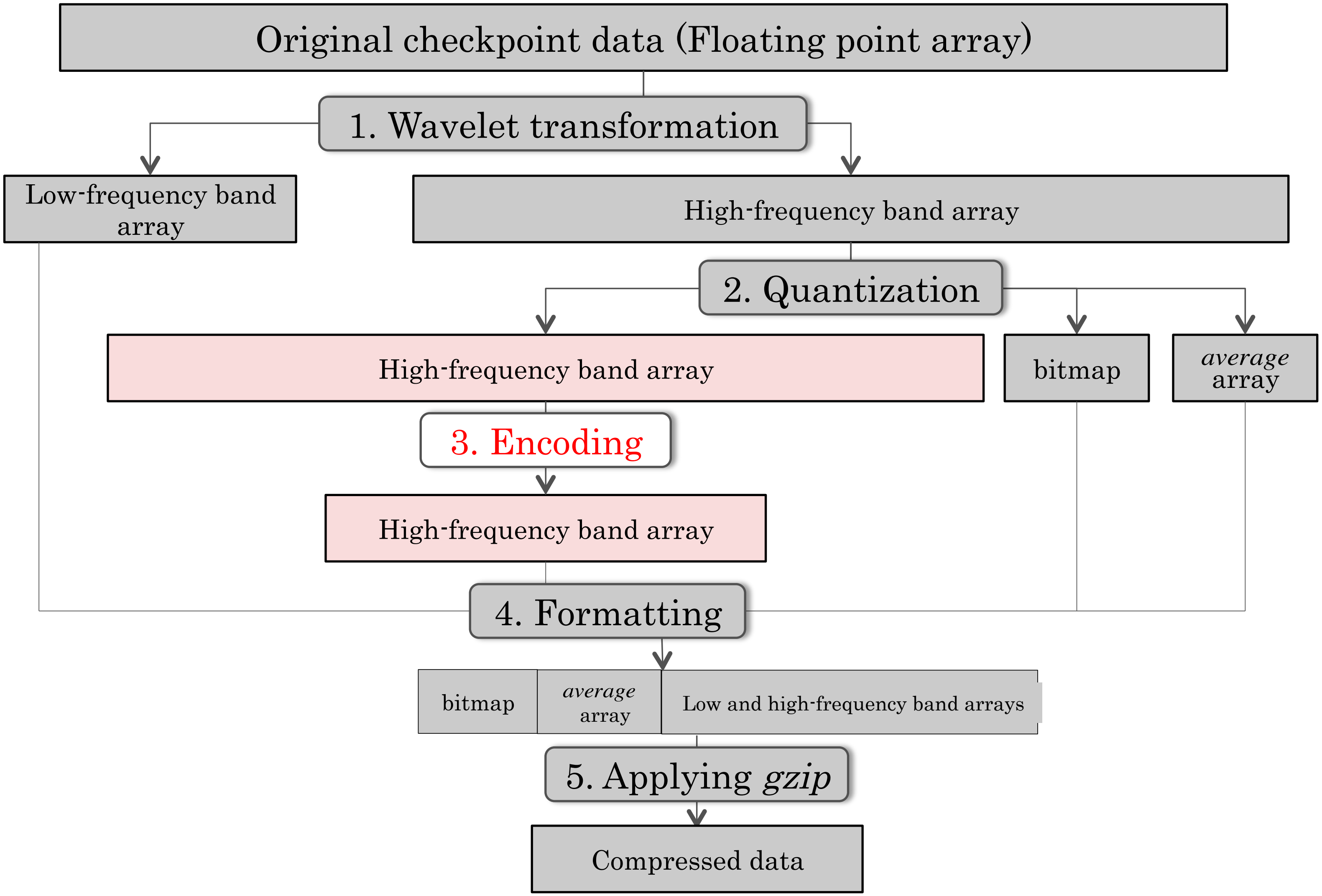
Simple quantization

- Replace all values in high-frequency band
  - →Introduce large errors
  - →High compression rate because of less type of values

Proposed quantization

- Replace parts of values in high-frequency band
  - →Introduce small errors
  - →Low compression rate by lack of regularity

Encoding

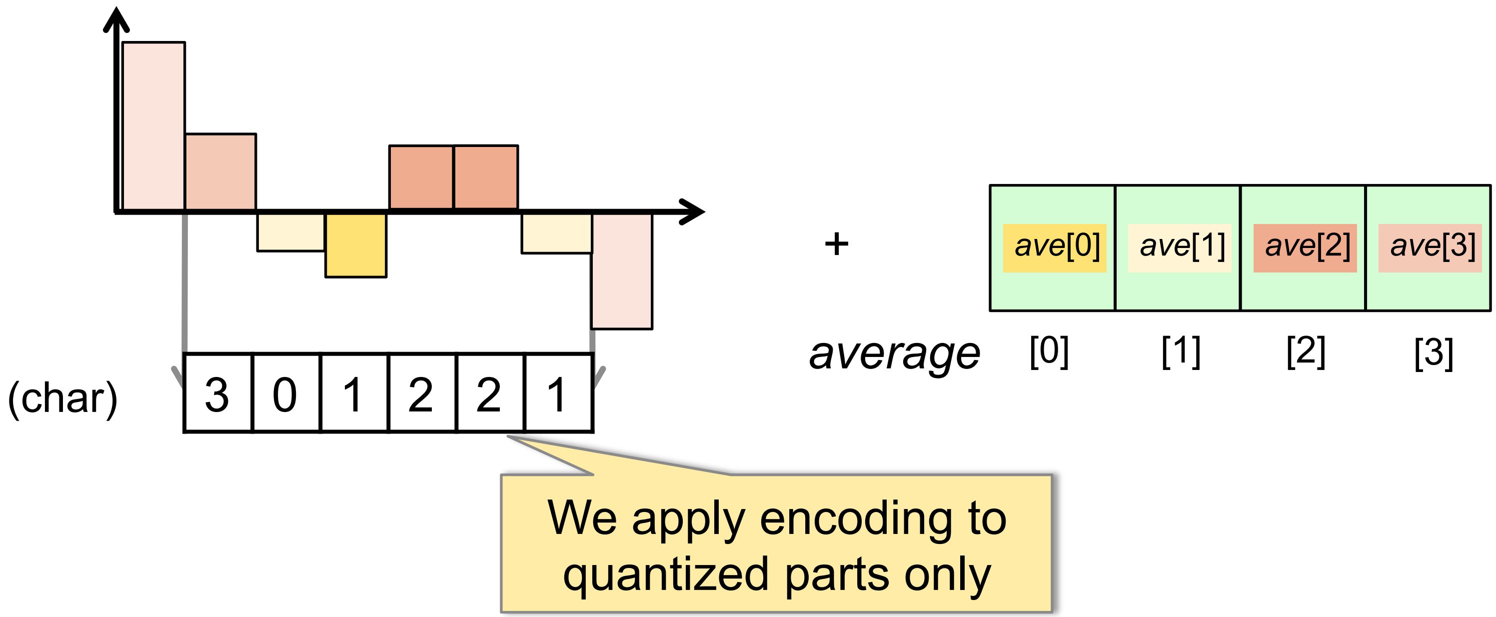

Original checkpoint data (Floating point array)
1. Wavelet transformation
Low-frequency band array
High-frequency band array
2. Quantization
High-frequency band array
bitmap
average array
3. Encoding
High-frequency band array
4. Formatting
bitmap
average array
Low and high-frequency band arrays
5. Applying *gzip*
Compressed data

Encoding

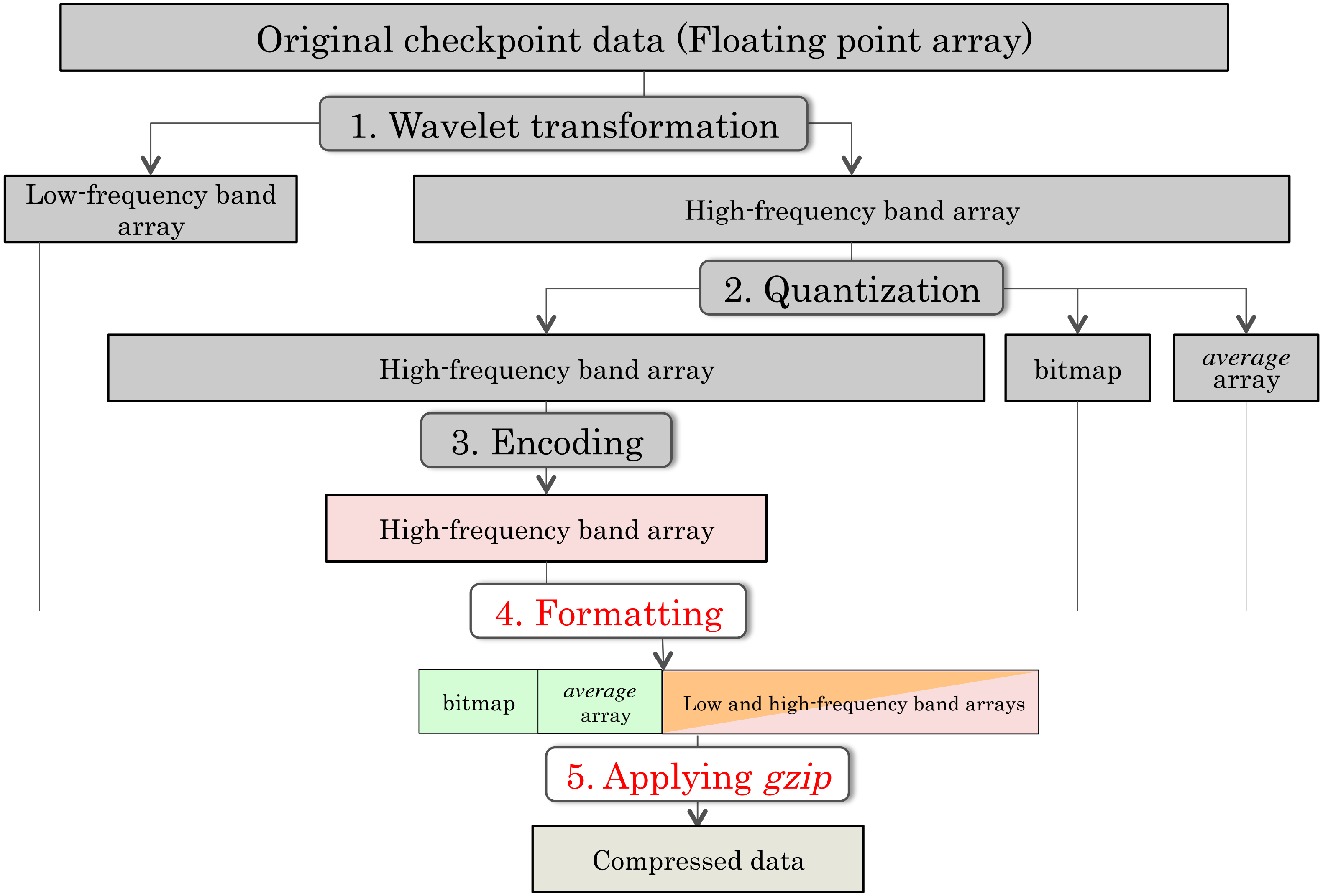
In quantization step, all or part of high-frequency band are replaced with *n* kinds of values

- *n* kinds of *double* values are replaced with corresponding *char* values
  - In case of *double,* data size becomes 1/8
  - In case of *float,* data size becomes 1/4

In recovery, an *average* array is required



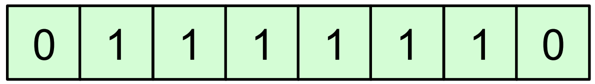
Formatting


Original checkpoint data (Floating point array)
1. Wavelet transformation
Low-frequency band array
High-frequency band array
2. Quantization
High-frequency band array
bitmap
average array
3. Encoding
High-frequency band array
4. Formatting
bitmap
average array
Low and high-frequency band arrays
5. Applying *gzip*
Compressed data

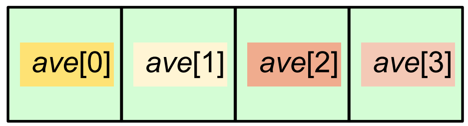
Recoverable Format

Required data in restart

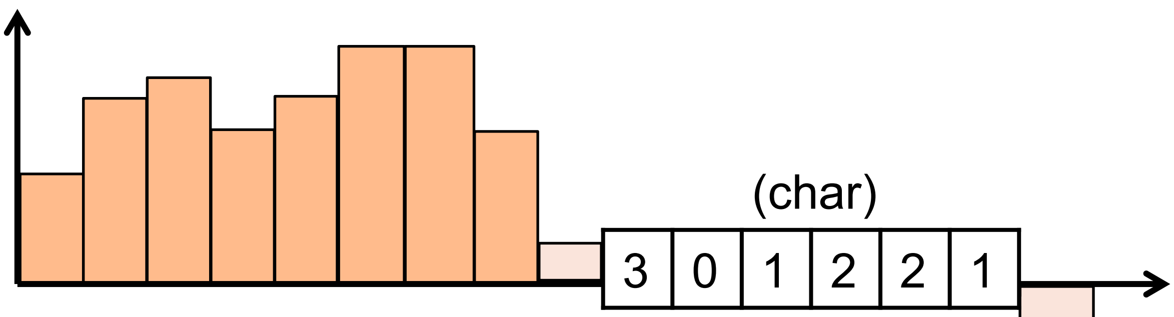
- Bitmap



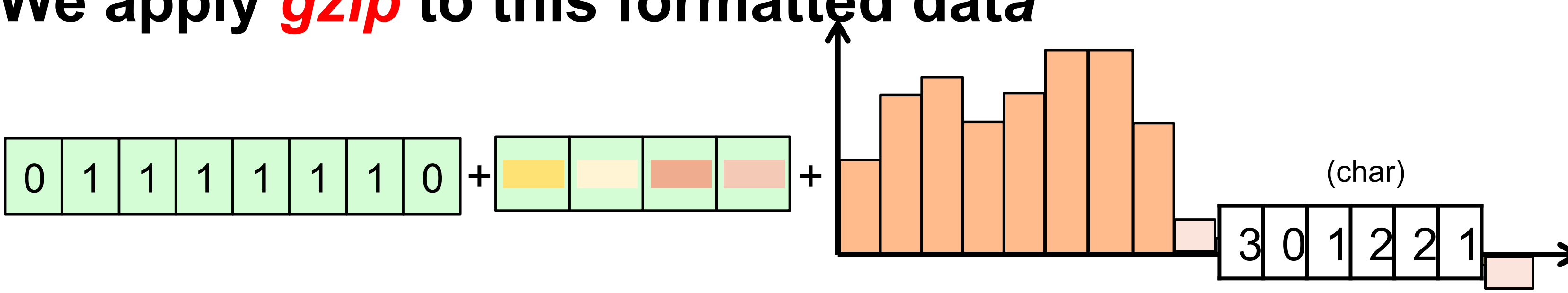
- Average array



- *Char* and *double* data to which is applied our approach

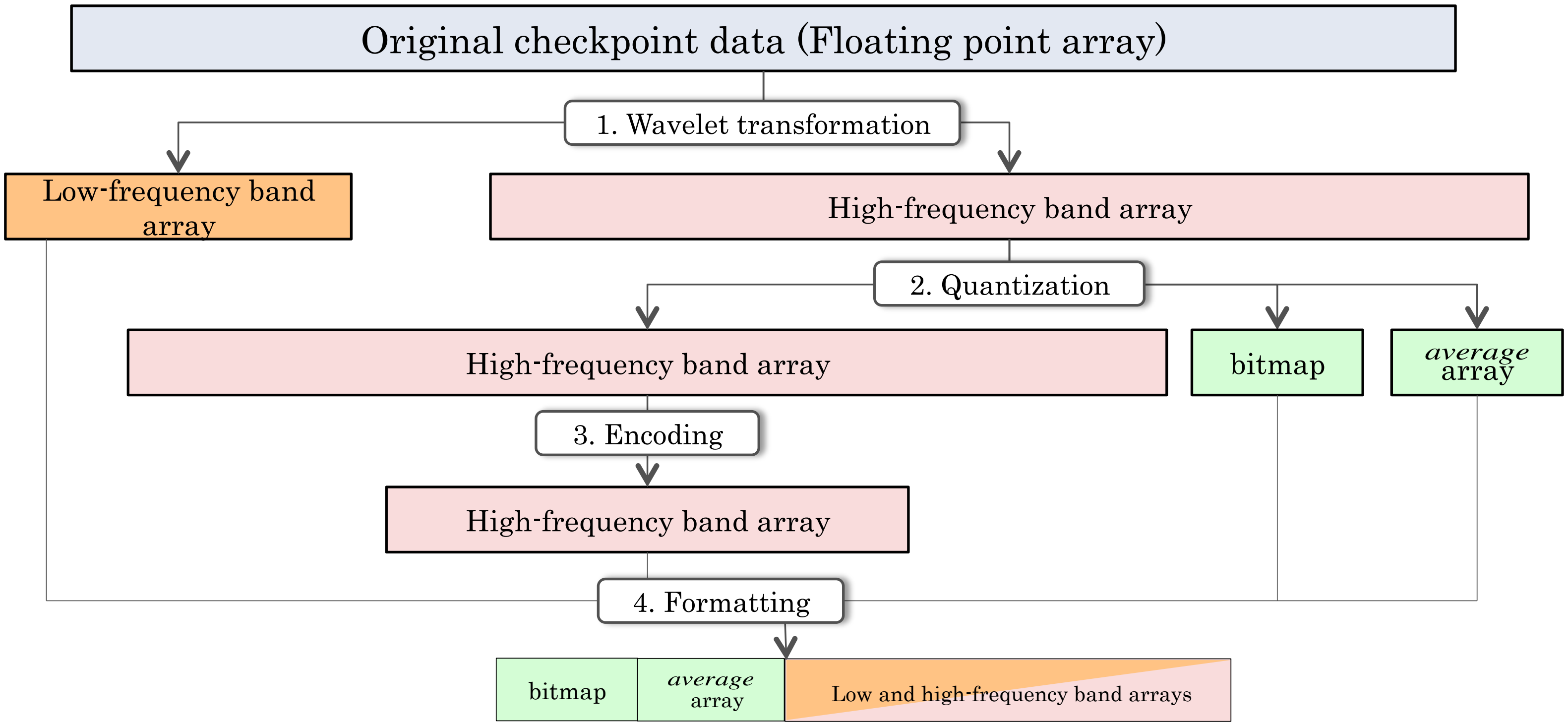


We apply *gzip* to this formatted data



Computational Complexity

Our compression algorithm contains only single loop that processes all or part of arrays

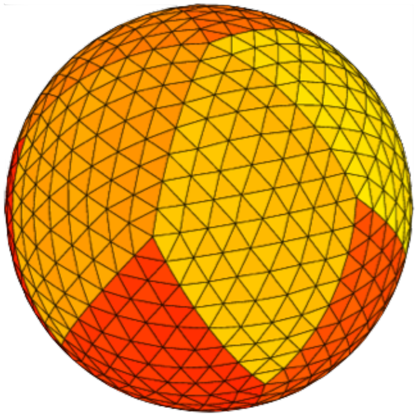


An algorithm of our approach has computational complexity *O(s)* with checkpoint size *s*

Evaluation Environment

To estimate a impact of our approach, we evaluate…

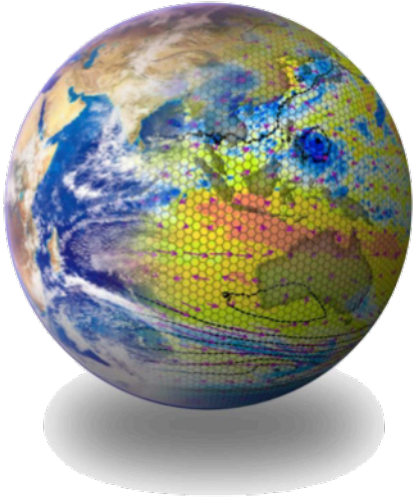
- Compression time
- Compression rate
- The degree of errors



Our approach is applied to real climate simulation, NICAM[M.Satoh, 2008]

- Target physical quantities are pressure, temperature and velocity.
    - double precision, 3Darray, 1156*82*2
- The data is too smooth in initial state

→apply our approach after 720 steps from initial state



Machine spec

CPU	Intel Core i7-3930K 6 cores 3.20GHz
Memory size	16GB

(citation of image : HPCS2014 全球大気シミュレーションにおいて、どこまで解像度が必要か？)

Metrics for Evaluation

Compression rate

$$CR = \frac{CS_{compressed}}{CS_{original}} \times 100[\%]$$

$CS_{compressed}$: checkpoint size with compression

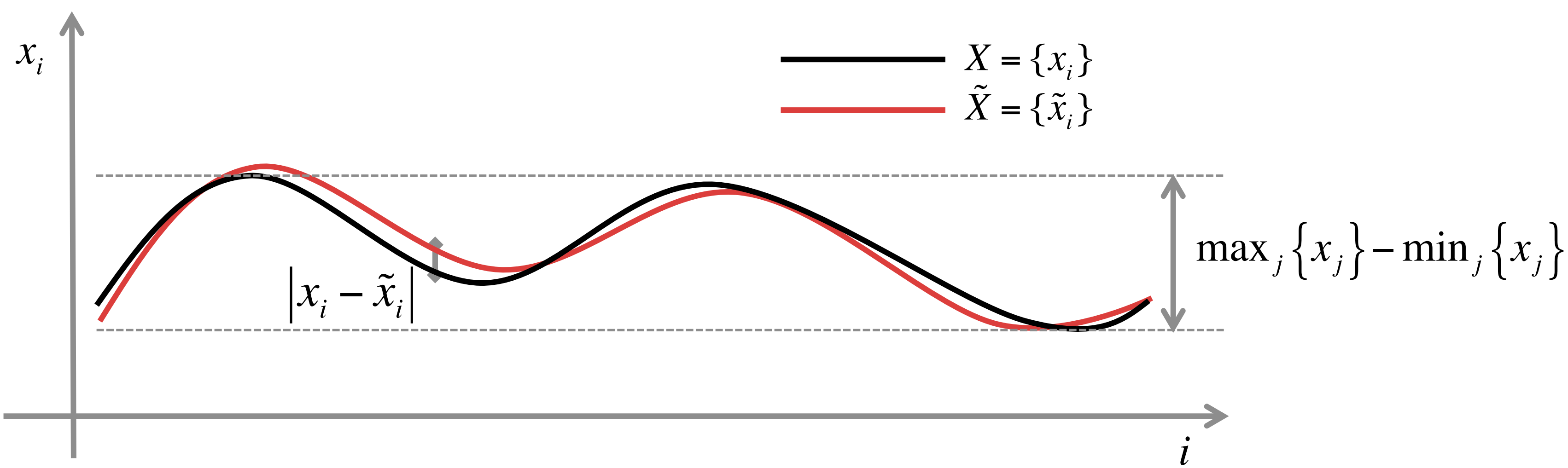
$CS_{original}$: original checkpoint size

Relative error

$$RE_i = \frac{|x_i - \tilde{x}_i|}{\max_j\{x_j\} - \min_j\{x_j\}}$$

$X = \{x_i\}$: original data

$\tilde{X} = \{\tilde{x}_i\}$: data with our approach



Evaluation of Compression Rate

Original checkpoint data
(Floating point array)

Apply *gzip*

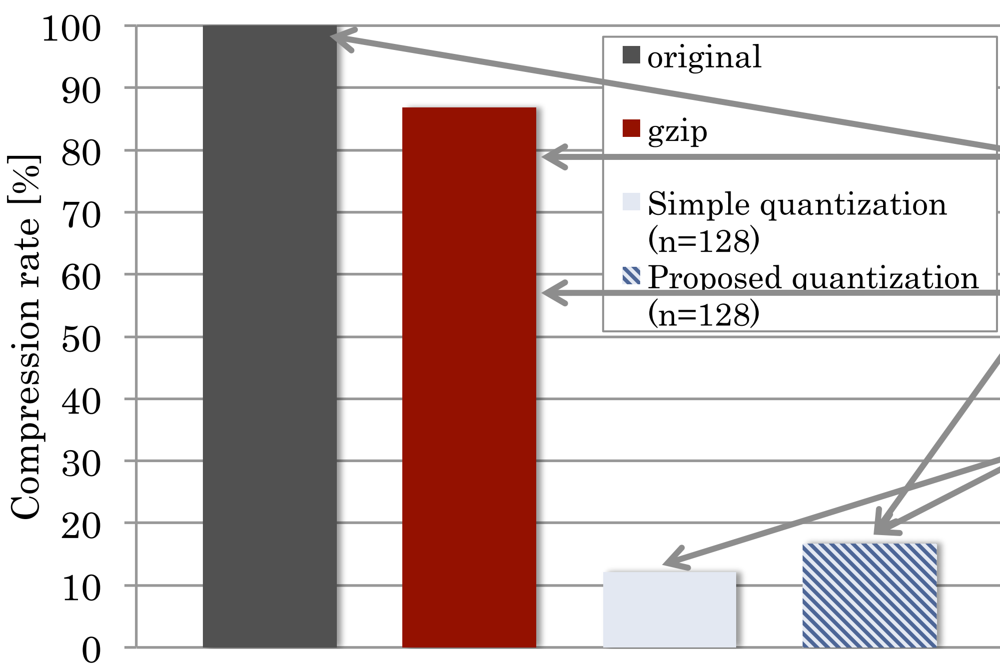
Compressed checkpoint data
with *gzip*

Apply our approach with simple quantization
(The number of division *n is 128*)

Compressed checkpoint data
with simple quantization

Apply our approach with proposal quantization
(The number of division *n is 128*)

Compressed checkpoint data
with proposal quantization



If we apply *gzip* to scientific checkpoint data directly, the size is reduced by about 13%

approach reduces checkpoint size by

Simple quantization achieves better compression rate, but introduces a larger error than proposal quantization

Evaluation of Errors

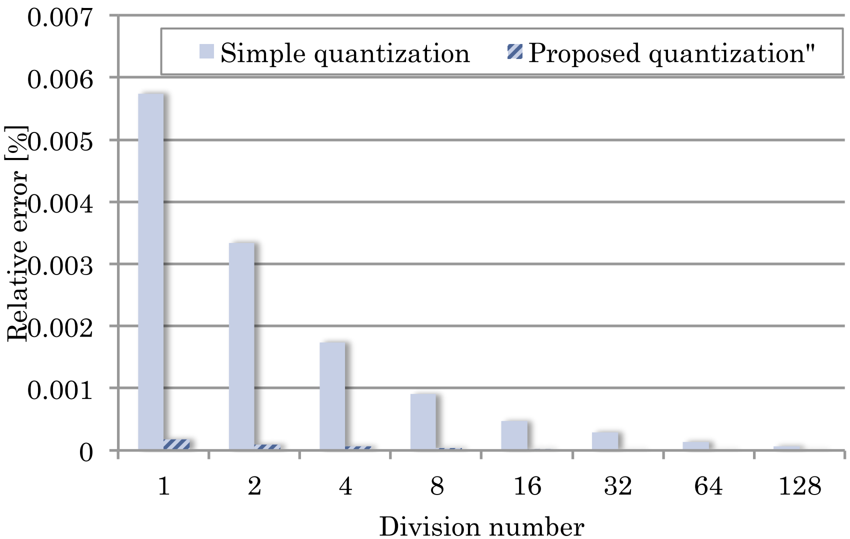
$$RE_i = \frac{x_i - \tilde{x}_i}{\max_j\{x_j\} - \min_j\{x_j\}}$$

Errors are reduced with # of division (*n*) increasing

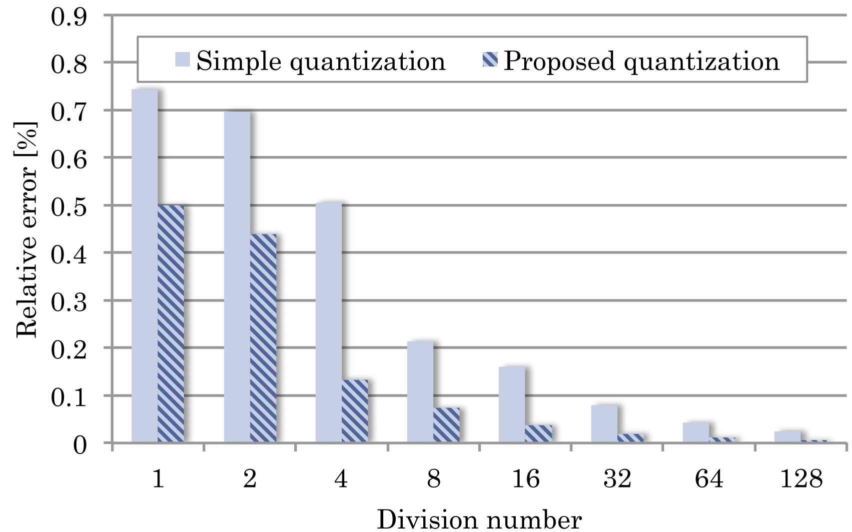
- Errors are reduced by about 98% at n = 128 compared with n = 1

Proposed quantization reduces an error compared with simple one

- The degree of reduction in errors is different depending on arrays



An average error on pressure array



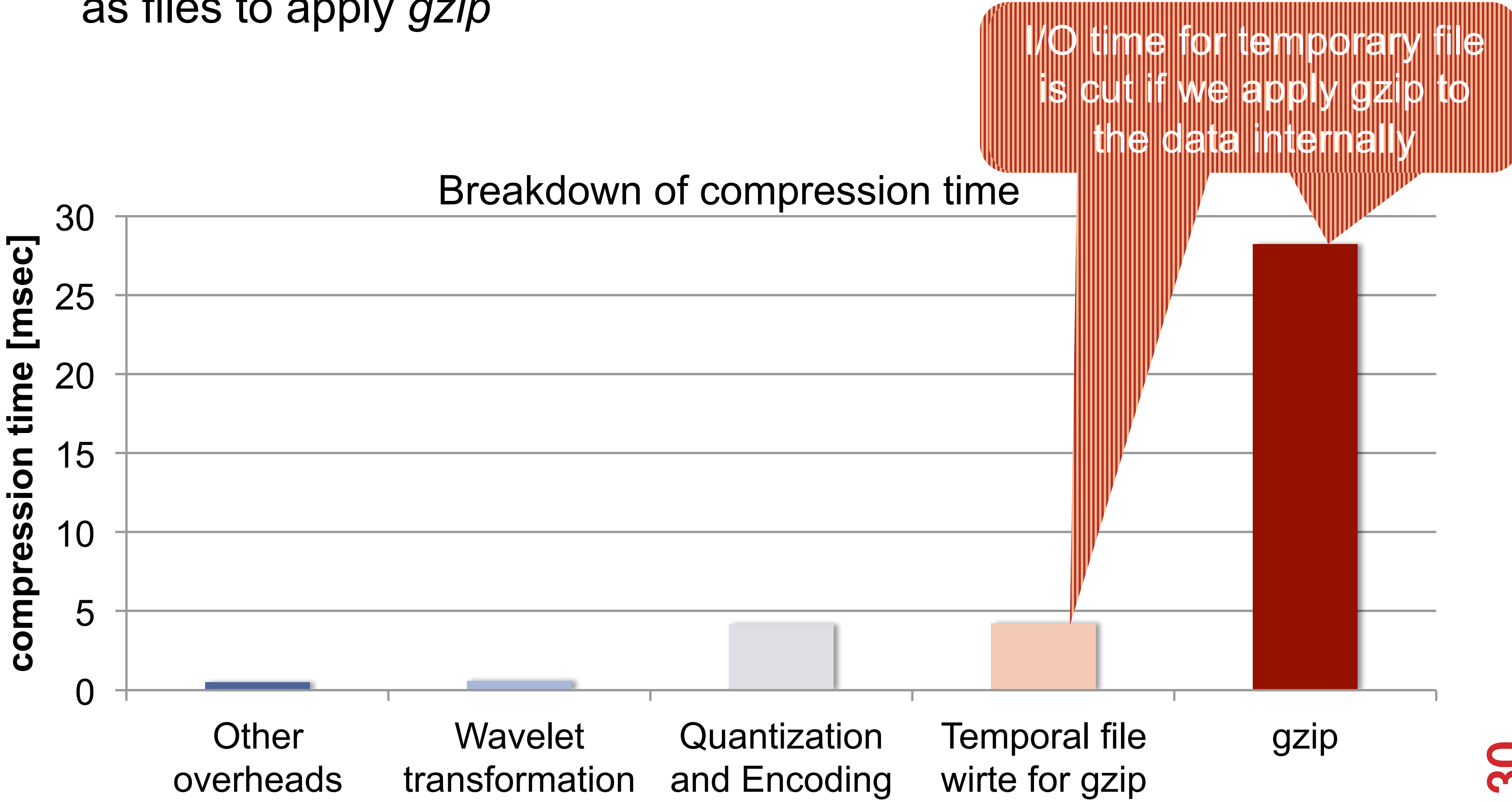
An average error on temperature array

On all variables, maximum errors are within 5% and average errors are within 1.2%

Evaluation of Compression Time

The figure shows breakdown of compression time

- The current implementation writes temporary file checkpoint data as files to apply *gzip*



Estimation on Massively Parallel Case

Assumptions for compression time

- I/O throughput…20GB/s
- Checkpoint size that each process has…about 1.5MB

  →Total checkpoint size…about (1.5 × # of parallelism)MB

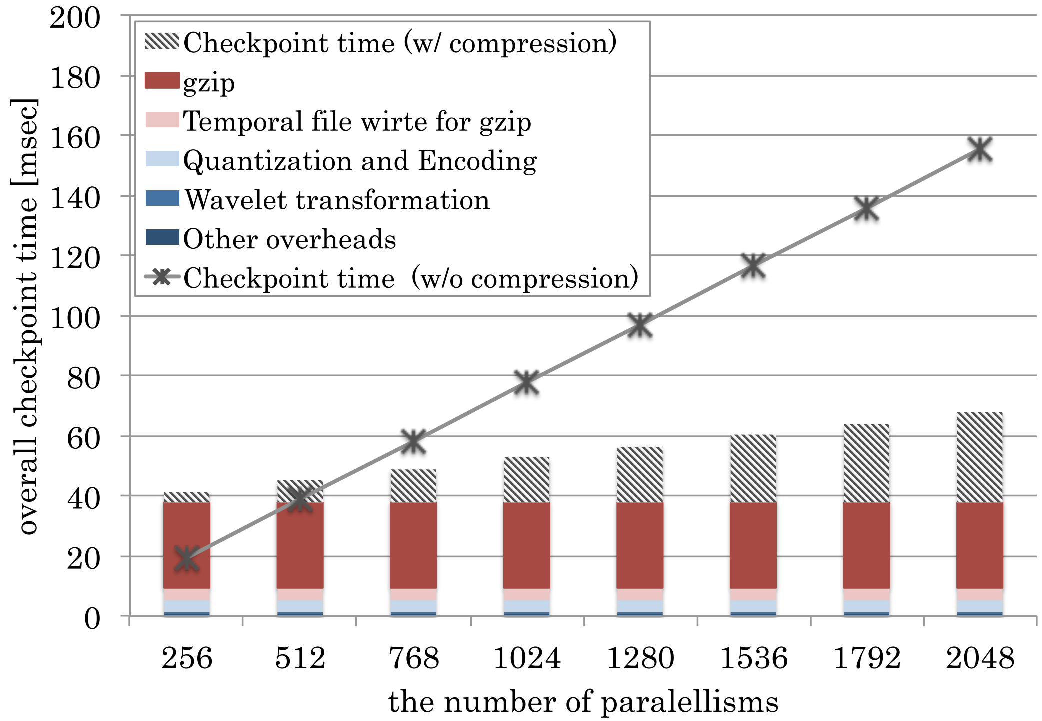
Actual survey

- Compression time
- Compression rate

Calculation from assumption

- I/O time

$$\frac{\text{Total checkpoint size}(\times \text{compression rate})}{\text{I/O Throughput}}$$



Estimation on Massively Pa

If compression time is negligible by increasing # of parallelism, I/O time reduces by about 81%

An assumption about compression time

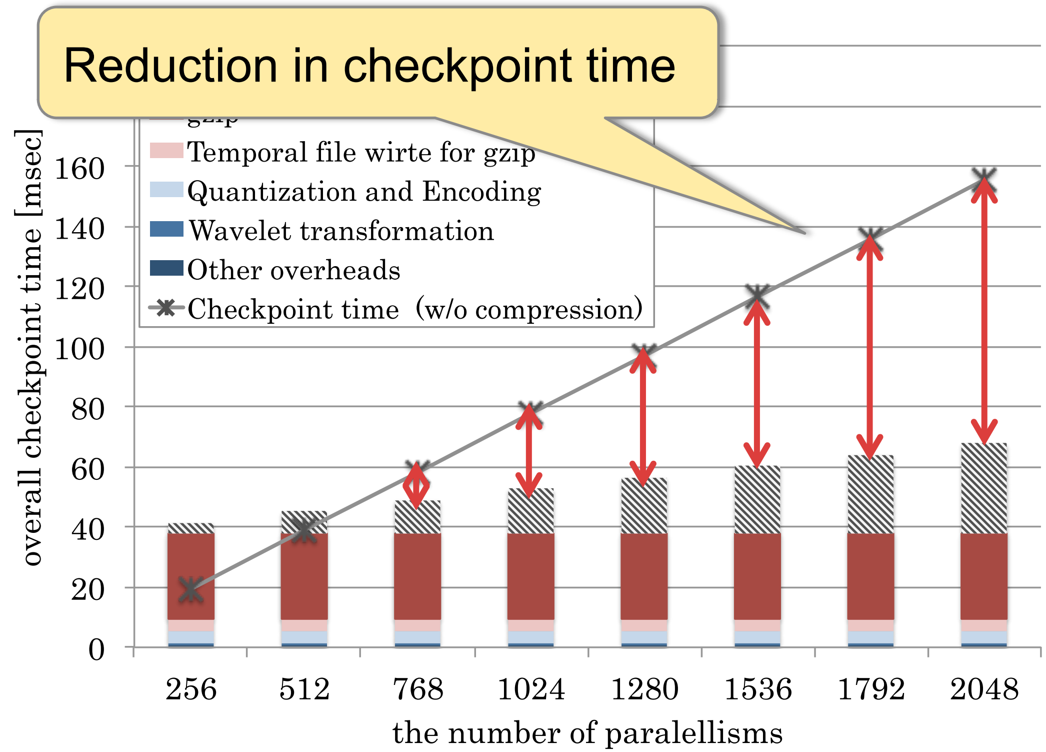
- I/O throughput…20GB/s
- Checkpoint size that each process has…about 1.5MB
  →Total checkpoint size…about (1.5 × # of parallelism)MB

Each process compresses 1.5MB checkpoint data in spite of # of parallelism

- Compression time is constant

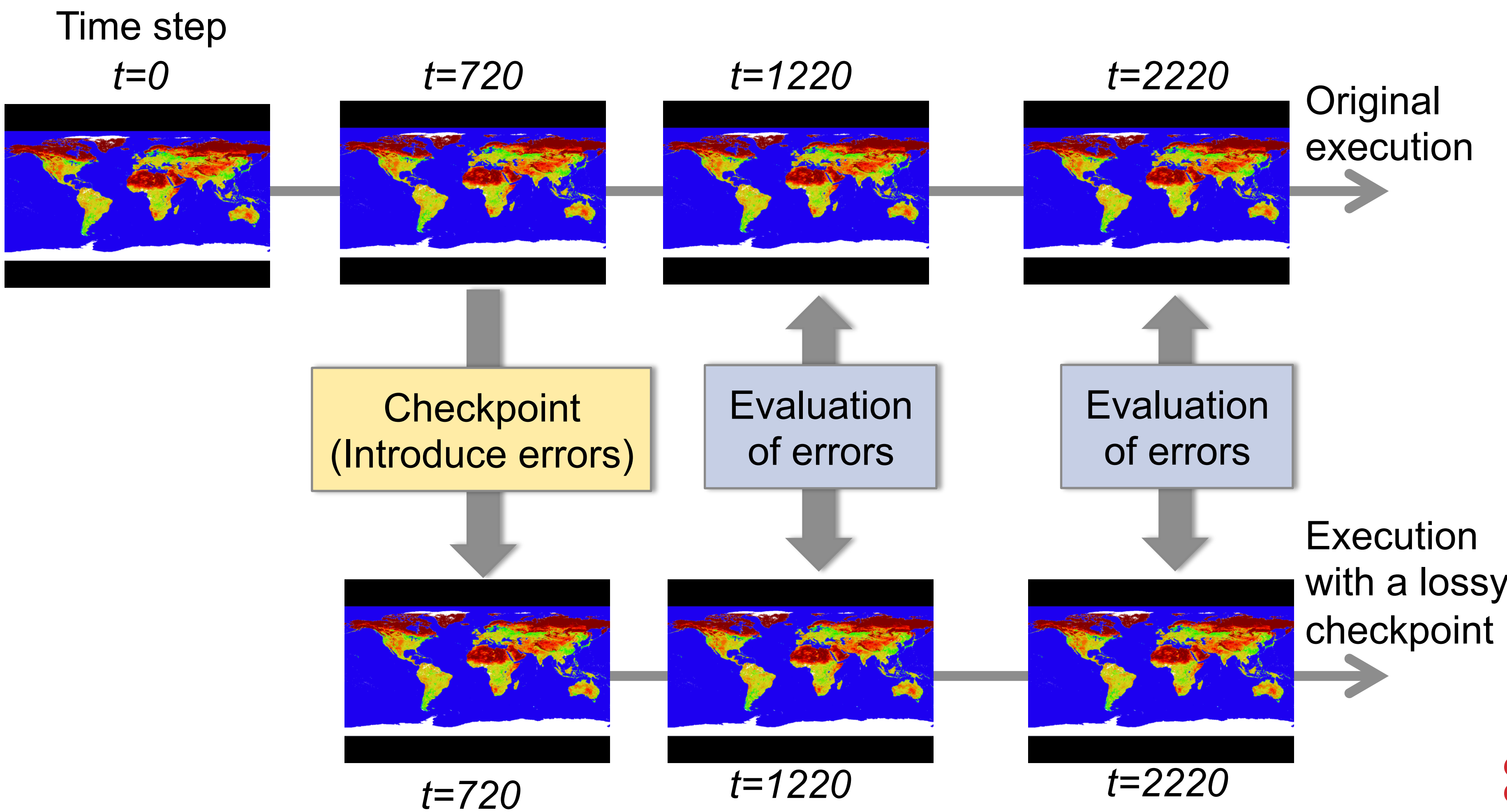
I/O time depends on total checkpoint size

Our approach takes advantage when # of parallelism increases



Evaluation Method for Error Transition

We evaluate error transition as shown in bottom figure



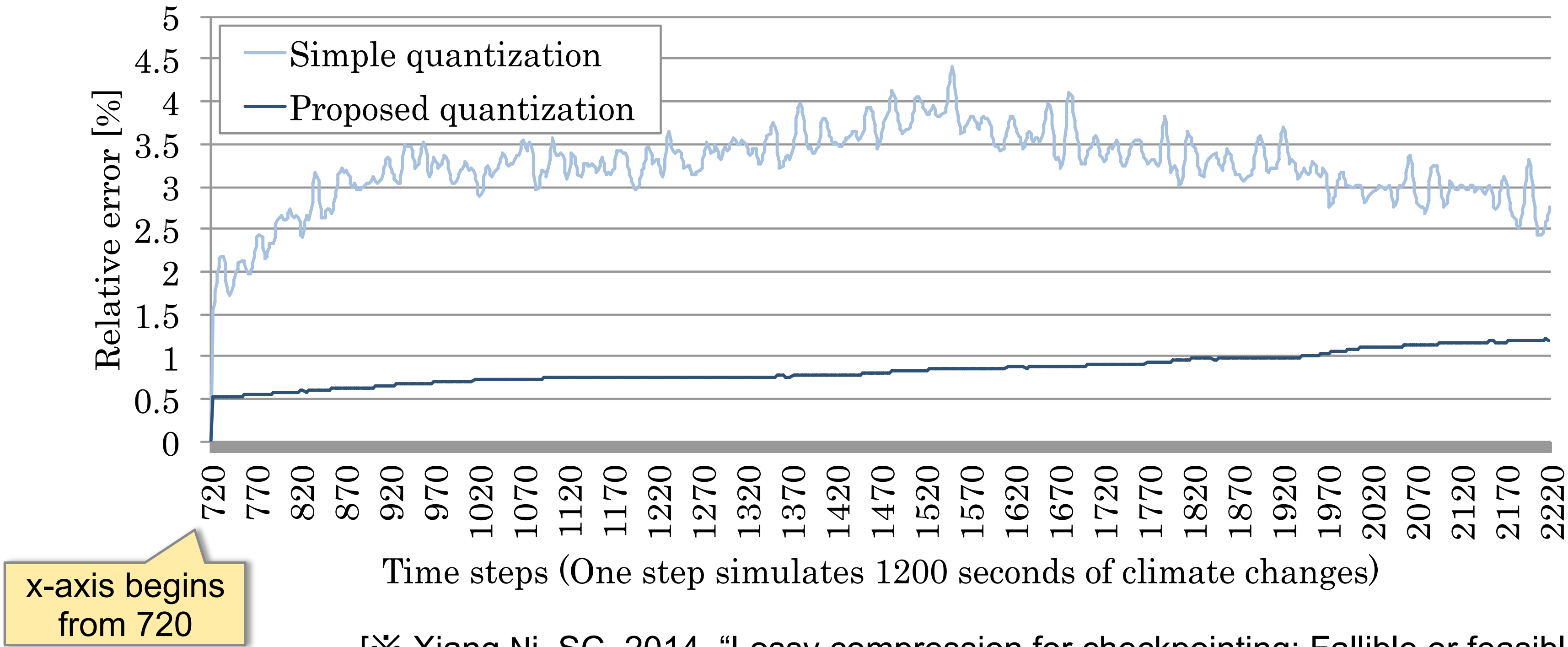
Evaluation of Error Transition

Lossy compression is applied to checkpoint data

→ Applications use the data with errors

→ The errors may diverge even if initial errors are small

Lossy compression has been becoming feasible for checkpoint image data in an N-body cosmology simulation [※]



[※ Xiang Ni, SC, 2014, "Lossy compression for checkpointing: Fallible or feasible?"]

Related Work

Multi-level checkpointing [Bautista-Gomez, SC, 2011]

- Applications write checkpoint to local storage frequently, and to parallel file system less frequently
- We can combine our approach with this technique

Incremental checkpointing [Naksinehaboon, CCGRID, 2008]

- This stores only differences with the last checkpoint
- We can combine our approach with this technique

MCREngine [Islam, SC, 2012]

- This study aims to improve compression rate with lossless compression
  - The scheme merges distributed checkpoint images per each variable, and select effective compression methods for each variable

Conclusion

Contribution

- We apply our approach to real climate application, NICAM, then overall checkpoint time included compression time is reduced by 81% with 1.2% relative error on average in particular situation
- We improve compression rate compared to lossless compression with the same degree of inherent errors to scientific simulations, such as sensor errors and model errors

Future work

- Improvement of the compression algorithm
    - Reduce compression rate and errors
- Investigation of the feasibility in other applications
- Combination with other efforts