4.8 EXPERIMENT OF A WAVELET-BASED DATA COMPRESSION TECHNIQUE WITH PRECISION CONTROL

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1. INTRODUCTION

With the development of computer hardware, observation networks, and numerical weather forecast model techniques, the size of the model data becomes increasingly large. A typical high-resolution model produces a few gigabytes of data everyday. In order to effectively transmit and store the model data, we need to consider and investigate some appropriate compression techniques.

The wavelet transform-based data compression technique has been successfully used in the compression of imagery data, such as satellite images. The traditional wavelet lossy compression schemes for imagery type data minimize mean squared error (MSE), which measures the 'overall' or 'average' error of the reconstructed images. The reconstructed images with small MSE usually contain only visually unnoticeable losses, and are considered 'meteorologically useful' in many applications. For model data, however, we need a more rigorous control of the losses, or errors. One common requirement is that the precision, or the magnitude of the maximum allowable round-off error has to be within a given threshold. This is a more difficult requirement to meet for wavelet transform-based (or other orthogonal transform-based) data compression.

With the same precision requirements, the compression scheme described in this article outperforms typical lossless codec (coder and decoder) by between 200%-600%.

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In this paper, we first give an overview of the special nature of model data. We then present our data compression scheme using wavelet transform-based data compression. Some preliminary test results are described.

This article ends with discussions of some practical issues and possible future research directions.

2. MODEL DATA

Model data are the grid data points that represent the atmospheric state. Compared to imagery data, model data have higher dimensionalities and relatively lower resolutions. For each parameter, there are three dimensions in space and one dimension in time. There is good correlation between the adjacent data points in all dimensions. Some weather data fields, such as temperature and wind speed, are relatively stationary, and more correlated, and thus more compressible, while others, like relative humidity, are relatively non-stationery, and less correlated, and thus less compressible. For the same field, the higher the vertical level, the smoother the field, in general. In particular, for most fields, the data close to the surface and tropopause tend to have more high frequency components, therefore they are more difficult to compress.

Apparently, for different fields, there are different requirements for the maximum round off errors. For this experiment, the following precision requirements are applied to the selected Eta-12 parameters:

- Temperature 2^{-3} K
- Relative Humidity 1 %

The above special nature and compression requirements of the model data warrant a special design for the codec, which should take advantage of the recent development of data compression technology while accommodating special needs of the datasets.

3. COMPRESSION SCHEME

Data compression with no loss, or near no loss has been studied for both transform-based and non transform-based schemes, in the context of imagery data (Karray et al. 1998, Wu and Bao 2000). Since most fields of our model are highly correlated along each dimension (especially horizontal dimensions), we believe that transform gain (Jayant and Noll 1984) will be significant, therefore the transform-based compression scheme should be the obvious choice.

Wavelet data compression consists of three steps: transform, quantization and entropy encoding. The first step decorrelates data so that information about the data is compacted into a few coefficients. The quantization step achieves bit rate reduction for the data, and also introduces loss (or errors) to the reconstructed data. The last step further reduces the size of the data with a lossless encoder.

Different error norms are used to measure the fidelity of the reconstructed data for lossy data compression. As we have mentioned in the introduction, most lossy image compression schemes use MSE as the error measure, which is equivalent to the L^2 norm error, while for model data, we want to specify a precision or threshold, which is equivalent to using L^∞ norm error.

For transform-based data compression, the quantization is performed in the coefficient domain. Since the Euclidean norm is invariant under orthogonal transform, it is straightforward to optimize the quantization so that the L^2 error of the reconstructed datasets is minimized. However, finding the optimal quantization to minimize the L^∞ error of the reconstructed datasets is much less straightforward. For a particular data point, the reconstruction error is bounded by the linear combination of the quantization errors of certain coefficients. Finding the optimal quantization step for an individual coefficient, or even for each subband, is time consuming and difficult. Besides, the resultant quantization step is usually too small to yield good compression. In addition, our operational environment has strict requirements for computation time. That prohibits us from optimizing the compression through any lengthy iterative process.

In our experiment, we use a rather simple scheme similar to the so-called *lossy plus lossless residual encoding* (Rabbani and Jones 1991) for lossless image compression. First we compress the data $\boldsymbol{f}$ minimizing error in the L^2 norm and compute the reconstructed data $\underline{\boldsymbol{f}}$. Then an error grid can be computed as the difference between the two $\boldsymbol{e} = | \boldsymbol{f} - \underline{\boldsymbol{f}} |$. We carefully entropy encode the critical information of the error grid into a compact bitstream, and append it to the bitstream of the lossy compression to make it a complete compressed dataset. On the decode side, the data $\underline{\boldsymbol{f}}$ is first reconstructed from the bitstream of the lossy compression, and then the losslessly encoded critical information of the error residuals are decoded and added back to the reconstructed datasets. This way we guarantee that no data point will have an error that exceeds the given threshold.

4. PRELIMINARY RESULTS

We have applied the above data compression procedure to the temperature and relative humidity field of the Eta-12 model. The reason for choosing these two fields is because they represent two typical fields of stationary and nonstationary meteorological data. To examine the differences between the fields at different height levels, we compress each frame individually with a different compression ratio. With L^∞ error controlled under a specified threshold, we plotted compression ratio of temperature and relative humidity fields at each pressure level in Figure 1 and Figure 2.

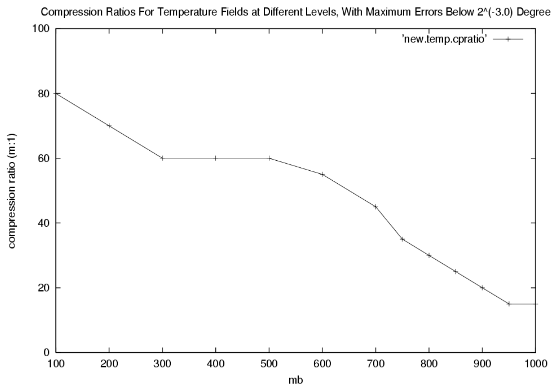

Fig. 1. The compression ratios for the temperature field at different pressure levels with controlled precision: L^{∞} error < 2^{-3} K.

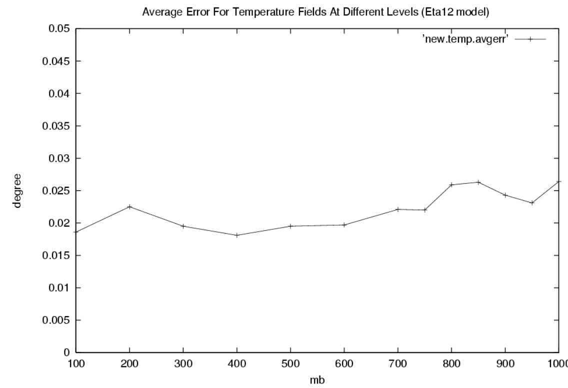

Fig. 3. Average errors for the temperature field at different pressure levels.

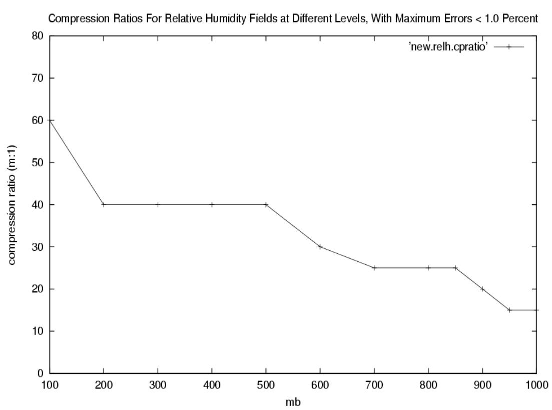

Fig. 2. The compression ratios for the relative humidity field at different pressure levels with controlled precision: L^{∞} error < 1%.

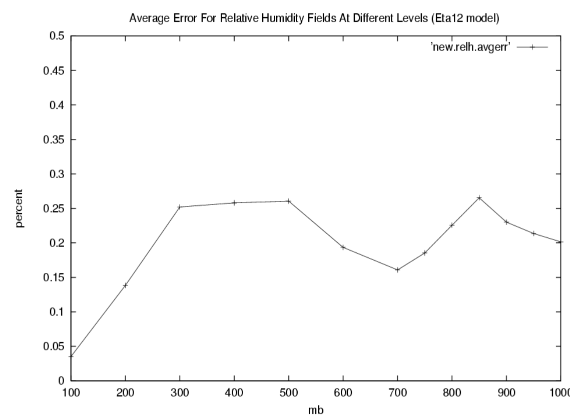

Fig. 4. Average errors for the relative humidity field at different pressure levels.

The average error reflects the overall quality of the reconstructed data. In Figures 3 and 4 we plotted the average errors, under the same compression ratios, for the two fields.

The compression test was done on an 850-MHz Pentium III desktop machine. The average compression time to encode each field (2.5 MB) is about 2-3 seconds.

5. CONCLUSION

For a given precision requirement, a wavelet-based data compression technique was applied to the temperature and relative humidity fields of the Eta-12 model. With the maximum allowable error of 2^{-3} degrees Kelvin, the wavelet compression procedure achieved an average compression factor of 45:1 for the quasi-stationary temperature field. The same procedure was applied to the relative humidity field, which is non-stationary compared to the temperature field. For this field the maximum error was set at less than 1%. With this predefined precision, the data compression procedure achieved an average compression factor of 30:1.

Compared to typical lossless codecs, with the same precision requirements, our codec achieves 2 to 6 times higher compression ratio. It implies that for a typical model output sized 1 GB, if transmitted over a 1 Megabit per second communication channel, the transmission time can be reduced from about 2.8 hours to about half an hour.

The presented data compression scheme is asymmetric by nature. It takes more time to encode the data than to decode it. This asymmetry is beneficial to our practical implementation, since we usually have more computing power in the encoding machine than in the decoding machine.

During future development, we plan to focus on the following two aspects of the data compression scheme.

The approach to control the maximum round off error is computationally simple (or somewhat ad hoc). It is feasible with our current operational environment; however, an ideal algorithm should be able to find the best bits allocation that minimizes the L^∞ error. An efficient algorithm that finds that allocation is very useful both in theory and in practice.

The vertically and timely adjacent frames are highly correlated. Current results only reflect the compression performance of our scheme on the two-dimensional field (in the horizontal plane). We can apply three or four dimensional separable wavelet transform to the volume data. To meet the robust (error propagation control) requirement, we can possibly encode each partitioned group of coefficients individually into an independent bitstream, as in Creusere (1997), to build a more error-resilient codec.

5. ACKNOWLEGMENTS

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