Recovering Silent Data Corruption through Spatial Prediction

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High-performance computing applications are central to advancement in many fields of science and engineering. Central to this advancement is the supposed reliability of the HPC system. However, as system size grows and hardware components are run with near-threshold voltages, transient upset events become more likely. Many works have explored the problem of detection of silent data corruption. Recovery is often left to checkpoint-restart or application-specific techniques. This poster explores the use of spatial similarity to recover from silent data corruption. We explore eight reconstruction methods and find that Linear Regression yields the best results with over 90% of Linear Regression's corrections having less than 1% relative error.

Additional Key Words and Phrases: Silent Data Corruption, High-performance Computing, Forward Recovery, Data prediction, Exascale

ACM Reference Format:
Sarah Placke and Jon C. Calhoun (Advisor). 2020. Recovering Silent Data Corruption through Spatial Prediction. 1, 1 (January 2020), 4 pages. https://doi.org/10.1145/1122445.1122456

1 INTRODUCTION

High-performance computing (HPC) applications enable scientific discovery across many disciplines. However, as systems that use more complex components run a lower voltage, the rate of hardware failures can increase [8]. Silent data corruption (SDC), results when data is unintentionally altered due to hardware failures. This typically results in bit-flips in the data. If not recovered, SDC propagates inside the application and potentially corrupts the application's output [2].

To detect the presence of SDC, many techniques have been developed — e.g., through redundancy, spatial/temporal prediction, preservation of physical phenomena. Once detection occurs, recovery typically proceeds via recovering from a checkpoint. However, knowing what data is corrupted allows for lower-cost localized recovery [5–7]. Prior approaches do not leverage higher-level information from the application to improve effectiveness.

Data prediction is an effective tool to detect SDC [1, 3]. Recently, spatial data prediction is used to significantly compress HPC data [4]. Because of its effectiveness of predicting data for HPC lossy data compression, we explore spatial data prediction for localized SDC recovery.

This poster makes the following contributions:

- investigates low-cost spatial prediction techniques to recover from SDC;
- demonstrates the relationship between data set smoothness and reconstruction accuracy; and
- shows Linear Regression is an accurate reconstruction method for SDC with over 90% of its corrections having less than 1% relative error.

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2020. XXXX-XXXX/2020/1-ART $15.00
https://doi.org/10.1145/1122445.1122456

2 BACKGROUND AND METHODOLOGIES

HPC simulations use numerical methods that leverage spatially contiguous properties to advance the simulation's state from time-step to time-step. Prior work explores the use of spatial and temporal smoothness to predict regions of likelihood for the simulations data: flagging SDC if the computed data falls outside the prediction region [1, 3]. Other work seeks to recover from point-wise corruption in data registers or location memory by attempting to reconstruct or replace the erroneous datum [5–7].

We improve over prior reconstruction work by leveraging higher-level information from the application. If we know the dimensionality of a memory allocation, we can employ multi-dimensional spatial prediction and regression functions to attempt to reconstruct the data. To accomplish this, we replace memory allocation calls with wrapper calls that record the starting address of a memory allocation and its dimensional size. When notified by the system that there is an uncorrectable error at a given memory location, we consult our allocation table to determine the spatial neighbors of the erroneous location. Once discovered, we reconstruct the data using various prediction functions.

3 EXPERIMENTAL RESULTS

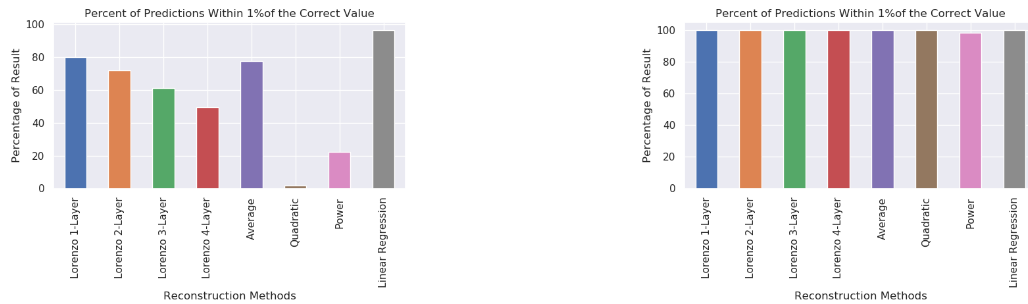
We quantify the effectiveness of the spatial prediction techniques using real-world HPC data from NYX and CESM. These applications respectfully produce three-dimensional and two-dimensional data. Experiments are run on Clemson's Palmetto Cluster. SDC is simulated by intentionally flipping random bits within each data set. In each test case, five percent of the data is corrupted at known locations, and we use reconstruction methods to correct the altered data. We showcase the accuracy of each method by analyzing the discrepancies between the predicted and correct values.

We evaluate the following reconstruction methods: n-layer Lorenzo prediction, averaging, quadratic-fit, power-fit, and linear regression-fit. Multi-dimensional methods such as n-layer Lorenzo prediction and averaging utilize neighboring values across all dimensions for prediction while the one-dimensional methods only utilize neighboring values within the first dimension. Each model utilizes varying amounts of spatial data, and we evaluate the effectiveness of each model by monitoring the relative error as well as the absolute deviation between the correct and predicted value.

3.1 Reconstruction Accuracy

Figure 1 shows the percentage of predictions within 1% of the correct values. There are three overall trends with respect to these percentages. Part a of Figure 1 shows the first trend where the linear regression-fit has the highest percentage and the remaining methods have varied accuracy. This trend demonstrates that linear regression has the best overall accuracy. The second trend is represented in part b of Figure 1. This presents a more uniform result among the reconstruction methods which is due to the content of the data sets. They contain numerous zero values, and non-zero values have small deviations from neighboring values. This shows the relationship between data set content and reconstruction accuracy. Data sets with greater spatial smoothness produce higher uniform accuracy. Therefore, there is a directly proportional relationship between the spatial roughness of a data set and its dependence on each reconstruction method for accuracy. This dependency is demonstrated in the third trend which has a high-accuracy linear regression-fit with the remaining reconstruction methods having greater than 20% relative error.

In NYX, the baryon density file maps baryon distribution across a constellation which displays the placement of baryonic matter, and the AEROD file in CESM maps the aerosol optical depth along a given field. These particular data sets were chosen because they best demonstrate the overall accuracy of each method when data is not spatially smooth as well as the relationship between



(a) Percent of reconstruction trials with less than 1% relative error for Baryon Density from the NYX dataset.

(b) Percent of reconstruction trials with less than 1% relative error for AEROD from the CESM dataset.

Fig. 1. Percentage of Predicted Values within 1% of Correct Values

spatial smoothness and uniform accuracy. The accuracy ranking of the reconstruction methods fluctuated among other data sets because the overall pattern(s) of the internal data fluctuate. (Some data sets model a quadratic model rather than a power model, so the quadratic-fit method would produce more accurate predictions.)

4 CONCLUSION

Silent data corruption is a high-risk corruption issue that can skewer simulation results. While checkpoint-restart or unique application techniques are functional solutions, low-cost spatial recovery is a valuable combatant for SDC correction. Our approach utilizes eight reconstruction methods: n-layer Lorenzo prediction, averaging, quadratic-fit, power-fit, and linear regression-fit. Each reconstruction method utilizes local data to reconstruct the corrupted value through prediction. Results show that the linear regression-fit is the most accurate reconstruction method with over 90% of its predictions within 1% of the correct value. However, discrepancies between individual reconstruction method accuracy decrease in proportion to the data set's spatial smoothness. (Data sets with greater spatial smoothness produce higher uniform accuracy.) These results demonstrate that spatial recovery is effective in mitigating the negative influences of SDC and improve the accuracy of large scale applications by successfully recovering silently corrupted data.

ACKNOWLEDGMENTS

Clemson University is acknowledged for generous allotment of compute time on the Palmetto cluster. This material is based upon work supported by the National Science Foundation under Grant No. SHF-1910197.

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