### Cost Estimation Algorithms for Dynamic Load Balancing of AMR Simulations



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### **Uintah Parallel Computing Framework**

- Uintah far-sighted design by <u>Steve Parker</u> :
  - Automated parallelism
    - Engineer only writes "serial" code for a hexahedral patch
    - Complete separation of user code and parallelism
    - Asynchronous communication, message coalescing
  - Multiple Simulation Components
    - ICE, MPM, Arches, MPMICE, et al.
  - Supports AMR with a ICE and MPMICE
  - Automated load balancing & regridding
  - Simulation of a broad class of fluid-structure interaction problems







# Uintah **Applications**



**Plume Fires** 



Angiogenesis



**Shaped Charges** 

**Industrial Flares** 



OF UTAH



Virtual Soldier

### How Does Uintah Work?







Patch-Based Domain Decomposition



### How Does Uintah Work?



### Legacy Issues

- Uintah is 12+ years old
- How do we scale to today's largest machines?
  - Identify and understand bottlenecks
    - TAU, hand profiling, complexity analysis
    - Reduce O(P) Dependencies
      - Look at memory footprint?
  - Redesigned components for O(100K) processors
    - Regridding, Load Balancing, Scheduling, etc





## **Uintah Load Balancing**

- Assign Patches to Processors
  - Minimize Load Imbalance
  - Minimize Communication
  - Run Quickly in Parallel
- Uintah Default: Space-Filling Curves
- Support for Zoltan

In order to assign work evenly we must know how much work a patch requires









#### **Cost Estimation: Performance Models**

E<sub>rt</sub>: Estimated Time

**G**<sub>r</sub>: Number of **Grid Cells** 

P<sub>r</sub>: Number of **Particles** 

$$\mathbf{E}_{r,t} = \mathbf{C}_1 \mathbf{G}_r + \mathbf{C}_2 \mathbf{P}_r + \mathbf{C}_3$$

**C**<sub>1</sub>, **C**<sub>2</sub>, **C**<sub>3</sub> : Model Constants

Need to be proportionally accurate

•Vary with simulation component, sub models, compiler, material, physical state, etc.

Can estimate constants using least squares at runtime

**G**<sub>n</sub>

$$\begin{bmatrix} G_0 & P_0 & 1 \\ \dots & \dots & \dots \\ G_n & P_n & 1 \end{bmatrix} \begin{bmatrix} C_1 \\ C_2 \\ C_3 \end{bmatrix} = \begin{bmatrix} O_{0,t} \\ \dots \\ O_{n,t} \end{bmatrix} \begin{bmatrix} C_1 \\ C_1 \\ C_2 \\ C_3 \end{bmatrix} \begin{bmatrix} O_{0,t} \\ \dots \\ O_{n,t} \end{bmatrix} \begin{bmatrix} C_{1} \\ C_{1} \\ C_{2} \\ C_{1} \end{bmatrix} \begin{bmatrix} C_{1} \\ C_{2} \\ C_{3} \end{bmatrix} \begin{bmatrix} C_{1} \\ C_{1} \\ C_{2} \\ C_{3} \end{bmatrix} \begin{bmatrix} C_{1} \\ C_{1} \\ C_{2} \\ C_{3} \end{bmatrix} \begin{bmatrix} C_{1} \\ C_{1} \\ C_{2} \\ C_{3} \end{bmatrix} \begin{bmatrix} C_{1} \\ C_{1} \\ C_{2} \\ C_{3} \end{bmatrix} \begin{bmatrix} C_{1} \\ C_{2} \\ C_{3} \end{bmatrix} \end{bmatrix} \begin{bmatrix} C_{1} \\ C_{2} \\ C_{3} \end{bmatrix} \begin{bmatrix} C_{1} \\ C_{2} \\ C_{3} \end{bmatrix} \end{bmatrix} \begin{bmatrix} C_{1} \\ C_{2} \\ C_{3} \end{bmatrix} \begin{bmatrix} C_{1} \\ C_{2} \\ C_{3} \end{bmatrix} \end{bmatrix} \begin{bmatrix} C_{1} \\ C_{2} \\ C_{3} \end{bmatrix} \end{bmatrix} \begin{bmatrix} C_{1} \\ C_{2} \\ C_{3} \end{bmatrix} \begin{bmatrix} C_{1} \\ C_{2} \\ C_{3} \end{bmatrix} \end{bmatrix} \begin{bmatrix} C_{1} \\ C_{2} \\ C_{3} \end{bmatrix} \end{bmatrix} \begin{bmatrix} C_{1} \\ C_{2} \\ C_{3} \end{bmatrix}$$

O<sub>r.t</sub>: Observed Time

Vhat if the constants

re not constant?



#### **Cost Estimation: Fading Memory Filter**

**E**<sub>r,t</sub>: **Estimated Time O**<sub>r,t</sub>: **Observed Time \alpha**: **Decay Rate** 

$$E_{r,t+1} = \alpha O_{r,t} + (1 - \alpha) E_{r,t}$$
$$= \alpha (O_{r,t} - E_{r,t}) + E_{r,t}$$

Error in last prediction

- No model necessary
- Can track changing phenomena
- May react to system noise
- Also known as:
  - Simple Exponential Smoothing
  - Exponential Weighted Average

#### **Compute per patch**



#### Cost Estimation: Kalman Filter, Oth Order

**E**<sub>r,t</sub>: Estimated Time **O**<sub>r,t</sub>: Observed Time

Update Equation: $E_{r,t+1} = K_{r,t} (O_{r,t} - E_{r,t}) + E_{r,t}$ Gain: $K_{r,t} = M_{r,t} / (M_{r,t} + \sigma^2)$ a priori cov: $M_{r,t} = P_{r,t-1} + \Phi$ a posteri cov: $P_{r,t} = (1 - K_{r,t}) M_{r,t}$  $P_0 = \infty$ 

- Accounts for uncertainty in the measurement:  $\sigma^2$
- Accounts for uncertainty in the model:  ${f \varphi}$
- No model necessary
- Can track changing phenomena
- May react to system noise
  - Faster convergence than fading memory filter



### **Cost Estimation Comparison**



Filters provide best estimateFilters spike when regridding





### **AMR ICE Scalability**

**Highly Scalable AMR Framework** 

**Even with small** problem sizes



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### AMR MPMICE Scalability



## Conclusions

- The complexity and range of applications within Uintah require an adaptable load balancer
- Profiling provides a good method to predict costs without burdening the user
- Large-Scale AMR requires that all portions of the algorithm scale well
- Through lots of work AMR within Uintah now scales to 100K processors
- A lot more work is needed to scale to O(200K-300K) processors





#### Questions?





