
EC500: Final Project

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1 INTRODUCTION

In this project, we solve in two dimensions the heat equation

$$\rho c_p \frac{\partial T}{\partial t} - \nabla \cdot (k \nabla T) = \dot{q}, \quad (1.1)$$

where

- k is a constant taken to be 1,
- ρ is the density of the medium (assumed to be constant),
- c_p is the specific heat of the medium (assumed to be constant),
- \dot{q} is the heat flux as a function of spacial coordinates (x, y) , and
- T is the temperature of the material as a function of spatial coordinates (x, y) and of time t .

In discrete form, the equation can be written as follows:

$$\rho c_p (T_{x,y,t+1} - T_{x,y,t}) - k(T_{x+1,y,t} + T_{x-1,y,t} + T_{x,y+1,t} + T_{x,y-1,t} - 4T_{x,y,t}) = \dot{q}. \quad (1.2)$$

The time step and spatial step have both been taken to be 1 in the finite difference approximations.

We now solve this problem using three different approaches:

- Red-black iteration, parallelized with OpenMP and MPI
- Conjugate gradient method
- Using a triangular lattice instead of a conventional square lattice

2 PARALLELIZED RED-BLACK

3 CONJUGATE GRADIENT METHOD

In order to use conjugate gradient (CG), we must write our problem in the form $\mathbf{A}\vec{x} = \vec{b}$ for vectors \vec{x} , \vec{b} and matrix \mathbf{A} . In this case, \vec{x} will be our temperature T , \vec{b} will be our heat flux \vec{q} and \mathbf{A} will encode the left-hand side of Equation 1.1. Note that we take $\frac{\partial T}{\partial t} = 0$ since we are only interested in the steady-state solution when using CG. We are therefore left with:

$$\mathbf{A}T_{x,y} = 4T_{x,y} - (T_{x+1,y} + T_{x-1,y} + T_{x,y+1} + T_{x,y-1}) = \vec{b} = \vec{q}. \quad (3.1)$$

Note that we make the time variable t implicit, since we no longer need it directly. The CG algorithm can now be applied as follows ¹:

Require: \mathbf{A} , \vec{b} , ϵ
Ensure: T

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 $T \leftarrow \vec{0}$ 
 $\vec{r} \leftarrow \vec{b} - \mathbf{A}T$  {residual}
 $\vec{p} \leftarrow \vec{r}$ 
loop
   $\alpha \leftarrow \frac{|\vec{r}|}{\vec{p} \cdot \mathbf{A}\vec{p}}$ 
   $T \leftarrow T + \alpha\vec{p}$ 
   $\vec{r}_{\text{new}} \leftarrow \vec{r} - \alpha\mathbf{A}\vec{p}$ 
  if  $|\vec{r}_{\text{new}}| < \epsilon$  then
    return  $T$ 
   $\beta \leftarrow \frac{|\vec{r}_{\text{new}}|}{|\vec{r}|}$ 
   $\vec{p} \leftarrow \vec{r}_{\text{new}} + \beta\vec{p}$ 
   $\vec{r} \leftarrow \vec{r}_{\text{new}}$ 

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Algorithm 1: Conjugate gradient algorithm

We take our initial guess T_0 to be zero everywhere. All that Algorithm 1 requires us to have is a way to perform dot products and a way of applying \mathbf{A} to a vector. The former is fairly trivial and the latter is given by Equation 3.1. With these fundamental operations at hand, it is straightforward to implement Algorithm 1 in code.

¹Adapted from https://en.wikipedia.org/wiki/Conjugate_gradient_method#The_resulting_algorithm

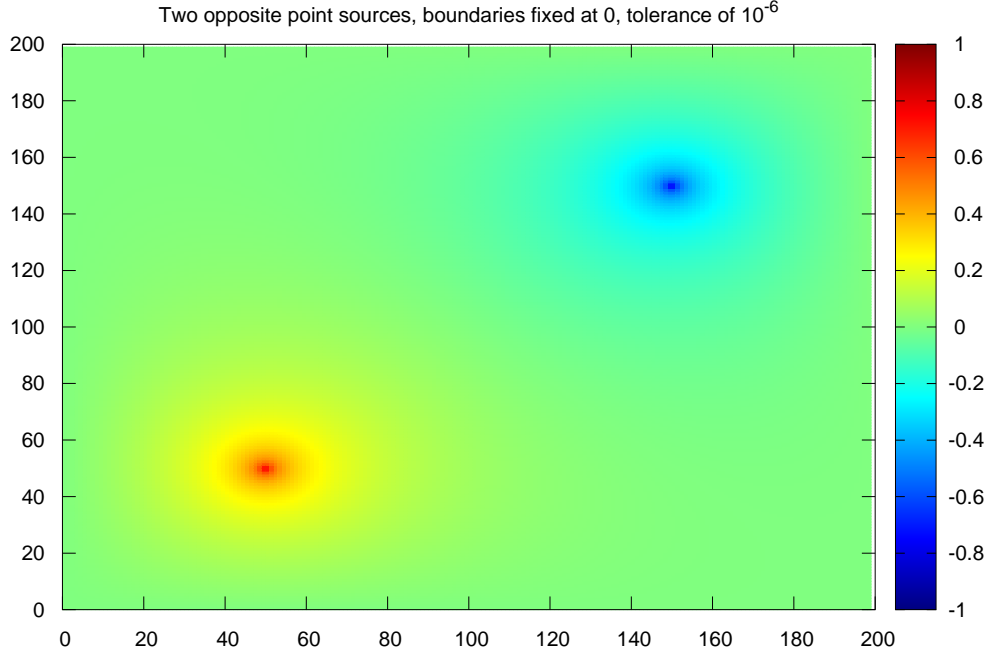


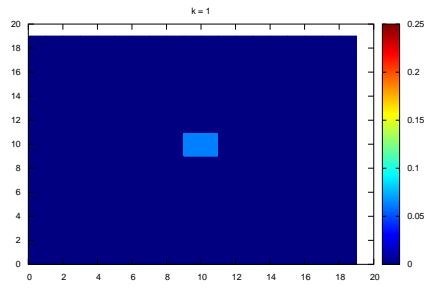
Figure 3.1: Final heat map for system with two point sources as shown, with boundaries fixed at zero. The point sources are equal in magnitude but opposite in sign.

Quick note on boundary conditions: We incorporate our boundary conditions in \vec{b} and apply \mathbf{A} only to the interior points of T – that is, points that have exactly four neighbors.

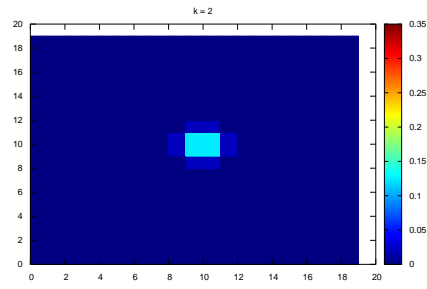
3.1 RESULTS

Figure 3.1 shows the result of applying the CG algorithm to a system with two opposite point sources on a 200-by-200 grid. The boundaries were fixed at zero and a residual tolerance of 10^{-6} was used. It is also instructive to view the result after each of the first few iterations of the main loop in Algorithm 1. Consider a simpler system with a single point source in the center on a 20-by-20 grid. The result after the first four iterations is shown in Figure 3.2. We can see from this figure how information propagates neighbor-by-neighbor from the source to the surrounding points. This makes sense since, by Equation 3.1, each non-zero point can only influence its closest neighbors on each iteration.

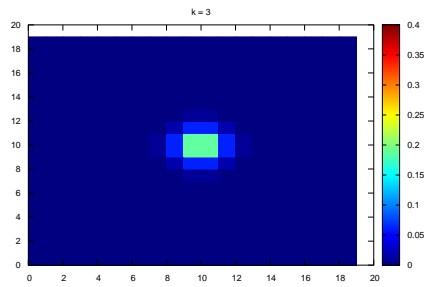
Finally, we compared timings of our conjugate gradient implementation to Gauss-Seidel iteration for several grid sizes, as shown in Figure 3.3. Clearly, conjugate gradient is a substantial algorithmic improvement over Gauss-Seidel.



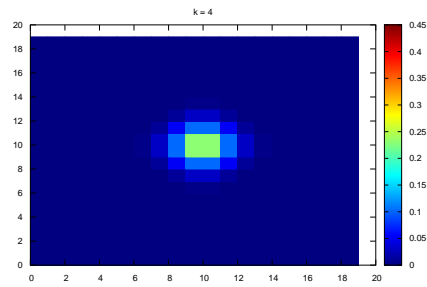
(a) $k = 1$



(b) $k = 2$



(c) $k = 3$



(d) $k = 4$

Figure 3.2: First four steps of conjugate gradient algorithm for system with a single point source in the center.

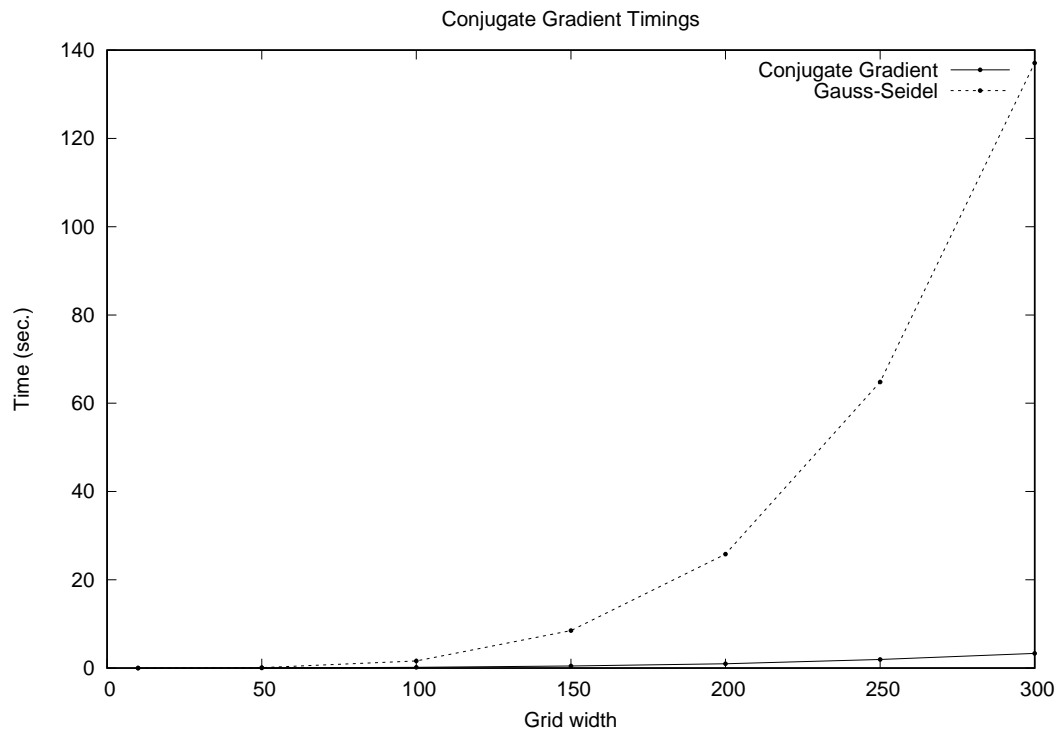


Figure 3.3: Timings for conjugate gradient as compared to Gauss-Seidel iteration for a system with a single point source in the center and a tolerance of 10^{-6} .

4 TRIANGULAR LATTICE

5 MISCELLANEOUS

5.1 CODE

The code for our project can be found at <https://github.com/winstonchen/ec500>.

5.2 CONTRIBUTIONS

- Ariya Shajii – Conjugate gradient
- Huy Le – Parallelized red-black iteration
- Winston Chen – Triangular lattice