Project 1 FYS3150

Anders P. Åsbø, Eivind Støland

We solved a simplified version of Poisson's equation numerically using three different algorithms based on linear algebra methods. We used a general Thomas algorithm, a specialized version of said algorithm for our problem, and LU decomposition and compared these three with execution times and relative error between the solutions they gave and an analytic one. The general Thomas algorithm uses approximately $8N$ FLOPs, the special Thomas algorithm uses approximately $6N$ FLOPs, and the LU decomposition uses something of the order $\frac{2}{3}N^3$ FLOPs, where N is the amount of steps. The measured execution times fits with these results. The calculated maximum relative error for the general Thomas algorithm is the same as that from the LU decomposition, and it is slightly larger for the special Thomas algorithm. Where as much precision as possible is needed this indicates that the general Thomas algorithm is the better choice of the three, but if less precision is needed and speed is prioritized the special algorithm is the best choice of the three.

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I. INTRODUCTION

One of the most versatile tools in modern science is numerical integration, thus it is important to understand its limits. In this paper we have performed numerical integration of a second order differential equation. This was done by discretizing the differential equation, and formulating it as a matrix-vector equation. The matrix-vector equation was then solved using both a general, and specialized Thomas algorithm, as well as LU-decomposition. Under the pretext of solving a 1D version of Poisson's equation, we have created and tested a numerical solver using the Thomas algorithm. Furthermore, we have compared our results with LU decomposition using the Armadillo library's solver. We measured the time spent by the various algorithms and their maximum relative error (to the analytic solution) in order to compare them quantitavely to see if they behave as expected.

II. FORMALISM

Poisson's equation is a well known equation from electromagnetism:

$$\nabla^2 \boldsymbol{\Phi}(\boldsymbol{r}) = -4\pi\rho(\boldsymbol{r})\,,$$

where $\boldsymbol{r}$ is the position, $\rho(\boldsymbol{r})$ is the charge density, and $\boldsymbol{\Phi}(\boldsymbol{r})$ is the electrostatic potential. If we assume spherical symmetry, this simplifies into a one-dimensional equation:

$$\frac{1}{r^2}\frac{d}{dr}\left(r^2\frac{d\boldsymbol{\Phi}}{dr}\right) = -4\pi\rho\,,$$

where $r = |\boldsymbol{r}|$. We can substitute $\boldsymbol{\Phi}(r) = \phi(r)/r$, which gives us:

$$\frac{d^2\phi}{dr^2} = -4\pi r\rho(r)$$

This is a second order differential equation which can be written generally as:

$$-u''(x) = f(x)\,,$$

where we have changed $r \to x$, $\phi \to u$ and $4\pi r\rho \to f(x)$. In order to proceed we need to pick a specific sample problem to be used. We choose to solve this equation with Dirichlet boundary conditions, meaning that $x \in (0,1)$ and $u(0) = u(1) = 0$. As for the source term

f we choose $f(x) = 100e^{-10x}$. This has the advantage of being possible to solve analytically:

$$\begin{aligned} -u''(x) &= f(x) \\ -u''(x) &= 100e^{-10x} \\ -u'(x) &= -10e^{-10x} - C \\ -u(x) &= e^{-10x} - Cx - D \\ u(x) &= Cx + D - e^{-10x}\,, \end{aligned}$$

where C and D are arbitrary constants. We use the boundary conditions in order to determine them:

$$\begin{aligned} u(0) &= 0 \\ \implies D - 1 &= 0 \\ D &= 1 \\ u(1) &= 0 \\ \implies C + 1 - e^{-10} &= 0 \\ C &= -(1 - e^{-10}) \end{aligned}$$

All in all this gives us that:

$$u(x) = 1 - (1 - e^{-10})x - e^{-10x}$$

Now we have an analytical solution we can compare our numerical solutions to later.

In order to solve the problem numerically we first need some definitions in order. We discretize with the grid points given by $x_i = ih$, in the interval from $x_0 = 0$ to $x_{n+1} = 1$. The step length is then given by $h = 1/(n+1)$. We name the discretized approximation to the solution v_i. We can then approximate the second derivative of u as:

$$-\frac{v_{i+1} + v_{i-1} - 2v_i}{h^2} = f_i\,,$$

where $f_i = f(x_i)$ and $i = 1, ..., n$. We look at some terms separately in order to find the matrix-vector form of this problem. First we look at the expression at the boundaries, starting with $i = 1$:

$$\begin{aligned} -\frac{v_2 + v_0 - 2v_1}{h^2} &= f_1 \\ 2v_1 - v_2 &= h^2 f_1 \\ 2v_1 - v_2 &= \tilde{b}_1\,, \end{aligned}$$

where we have defined a new variable $\tilde{b}_i = h^2 f_i$ and applied the relevant boundary condition. We then look at the expression when $i = n$:

$$\begin{aligned} -\frac{v_{n+1} + v_{n-1} - 2v_n}{h^2} &= f_n \\ -v_{n-1} + 2v_n &= \tilde{b}_n\,, \end{aligned}$$

where we also applied the relevant boundary condition. The general expression can also be rewritten as:

$$-v_{i-1} + 2v_i - v_{i+1} = \tilde{b}_i$$

This now clearly takes the shape of a matrix-vector problem. We define a vector $\mathbf{v}$ which contains all the v_i and similarly a vector $\tilde{\mathbf{b}}$ which contains all the b_i. The coefficients on the left-hand side of the equations determine a $n \times n$-matrix $\mathbf{A}$:

$$\mathbf{A} = \begin{bmatrix} 2 & -1 & 0 & ... & ... & 0 \\ -1 & 2 & -1 & 0 & ... & ... \\ 0 & -1 & 2 & -1 & 0 & ... \\ ... & ... & ... & ... & ... & ... \\ 0 & ... & ... & -1 & 2 & -1 \\ 0 & ... & ... & 0 & -1 & 2 \end{bmatrix}$$

The matrix-vector problem we need to solve then is:

$$\mathbf{A}\mathbf{v} = \tilde{\mathbf{b}}$$

$\mathbf{A}$ is a tridiagonal matrix. This means we can apply methods specialized for this kind of linear algebra problem. A tridiagonal matrix can be decomposed into three vectors, one for the diagonal and one each for the bands above and below the diagonal. We choose the vectors $\mathbf{a}$, $\mathbf{b}$ and $\mathbf{c}$. Their components are defined the following way:

$$\mathbf{A} = \begin{bmatrix} b_1 & c_1 & 0 & ... & ... & 0 \\ a_2 & b_2 & c_2 & 0 & ... & ... \\ 0 & a_3 & b_3 & c_3 & 0 & ... \\ ... & ... & ... & ... & ... & ... \\ 0 & ... & ... & a_{n-1} & b_{n-1} & c_{n-1} \\ 0 & ... & ... & 0 & a_n & b_n \end{bmatrix}$$

As the bands above and below the diagonal have one element less than the diagonal itself, we note that $\mathbf{a}$ and $\mathbf{c}$ both have $n - 1$ elements defined this way instead of n elements (as $\mathbf{b}$). We choose, however, to let $\mathbf{a}$'s first component to be denoted a_2, as the indexing then matches those along the same row of the matrix $\mathbf{A}$.

In general this gives us equations on the form:

$$a_i v_{i-1} + b_i v_i + c_i v_{i+1} = \tilde{b}_i\,,$$

which we need to solve. As there is no element c_n or a_1, we simply define them to be 0 instead, and thus the equation is valid from $i = 1, ..., n$. Looking at the tridiagonal matrix $\mathbf{A}$ with general elements again, we can see that we can eliminate the band below the diagonal (the components of $\mathbf{a}$). First we take the first row multiplied by a_2/b_1 and subtract it from row 2. This leaves us with the following matrix:

$$\mathbf{A} = \begin{bmatrix} b_1 & c_1 & 0 & ... & ... & 0 \\ 0 & b_2 - \frac{a_2 c_1}{b_1} & c_2 & 0 & ... & ... \\ 0 & a_3 & b_3 & c_3 & 0 & ... \\ ... & ... & ... & ... & ... & ... \\ 0 & ... & ... & a_{n-1} & b_{n-1} & c_{n-1} \\ 0 & ... & ... & 0 & a_n & b_n \end{bmatrix}$$

We now define $\tilde{d}_2 = b_2 - \frac{a_2 c_1}{b_1}$, and $\tilde{d}_1 = b_1$ in order to simplify further equations:

$$\mathbf{A} = \begin{bmatrix} \tilde{d}_1 & c_1 & 0 & ... & ... & 0 \\ 0 & \tilde{d}_2 & c_2 & 0 & ... & ... \\ 0 & a_3 & b_3 & c_3 & 0 & ... \\ ... & ... & ... & ... & ... & ... \\ 0 & ... & ... & a_{n-1} & b_{n-1} & c_{n-1} \\ 0 & ... & ... & 0 & a_n & b_n \end{bmatrix}$$

We can now similarly eliminate a_3 by multiplying row 2 with $\frac{a_3}{\tilde{d}_2}$ and subtract this from row 3. This gives us the following:

$$\mathbf{A} = \begin{bmatrix} \tilde{d}_1 & c_1 & 0 & ... & ... & 0 \\ 0 & \tilde{d}_2 & c_2 & 0 & ... & ... \\ 0 & 0 & b_3 - \frac{a_3 c_2}{\tilde{d}_2} & c_3 & 0 & ... \\ ... & ... & ... & ... & ... & ... \\ 0 & ... & ... & a_{n-1} & b_{n-1} & c_{n-1} \\ 0 & ... & ... & 0 & a_n & b_n \end{bmatrix}$$

We now define $\tilde{d}_3 = b_3 - \frac{a_3 c_2}{\tilde{d}_2}$. This process can be repeated until all the elements in the band below the diagonal are eliminated. The new diagonal elements ($\tilde{d}_i$) are given by the following formula:

$$\tilde{d}_i = b_i - \frac{a_i c_{i-1}}{\tilde{d}_{i-1}} \quad , \quad i = 2, ..., n \,,$$

with $\tilde{d}_1 = b_1$. This leaves us with a new matrix $\mathbf{A}$:

$$\mathbf{A} = \begin{bmatrix} \tilde{d}_1 & c_1 & 0 & ... & ... & 0 \\ 0 & \tilde{d}_2 & c_2 & 0 & ... & ... \\ 0 & 0 & \tilde{d}_3 & c_3 & 0 & ... \\ ... & ... & ... & ... & ... & ... \\ 0 & ... & ... & 0 & \tilde{d}_{n-1} & c_{n-1} \\ 0 & ... & ... & 0 & 0 & \tilde{d}_n \end{bmatrix}$$

Now in order for us to use this to solve the problem, it also needs to be applied to $\tilde{\mathbf{b}}$ simultaneously, resulting in a new vector $\tilde{\mathbf{f}}$ with elements given as:

$$\tilde{f}_i = \tilde{b}_i - \frac{a_i \tilde{f}_{i-1}}{\tilde{d}_{i-1}} \quad , \quad i = 2, ..., n \,,$$

with $\tilde{f}_1 = \tilde{b}_1$. This gives us equations on the following form that we need to solve:

$$\tilde{d}_i v_i + c_i v_{i+1} = \tilde{f}_i \quad , \quad i = 1, ..., n$$

We note that $c_n = 0$, which means that when $i = n$, we have that:

$$\tilde{d}_n v_n = \tilde{f}_n$$
$$v_n = \frac{\tilde{f}_n}{\tilde{d}_n}$$

Now that we know one value in $\mathbf{v}$, this will now uniquely determine the other elements. We can see this by rewriting:

$$\tilde{d}_i v_i + c_i v_{i+1} = \tilde{f}_i$$
$$v_i = \frac{\tilde{f}_i - c_i v_{i+1}}{\tilde{d}_i}$$

As long as we know the last element in $\mathbf{v}$ (which we do at this point) this relation allows us to find v_i for $i = n-1, ..., 1$. As we run through the elements from the largest i to the smallest we call this part the backwards substitution part. For similar reasons we call calculating the $\tilde{d}_i$ and $\tilde{f}_i$ the forwards substitution part. This algorithm is called the Thomas algorithm [1] and is used for solving a matrix-vector equation with a general tridiagonal matrix. In our case however, we know what the elements of $\mathbf{A}$ are, allowing us to form a specialized algorithm. First we look at the $\tilde{d}_i$:

$$\tilde{d}_i = b_i - \frac{a_i c_{i-1}}{\tilde{d}_{i-1}}$$

We recognize that $b_i = 2$, and $a_i = c_{i-1} = i - 1$. This simplifies the equation:

$$\tilde{d}_i = 2 - \frac{1}{\tilde{d}_{i-1}}$$
$$= \frac{i+1}{i}$$

We can simplify $\tilde{f}_i$ in a similar way:

$$\tilde{f}_i = \tilde{b}_i - \frac{a_i \tilde{f}_{i-1}}{\tilde{d}_{i-1}}$$
$$\tilde{f}_i = \tilde{b}_i + \frac{i-1}{i} \tilde{f}_{i-1}$$

This also gives us a simplification for v_i:

$$v_i = \frac{\tilde{f}_i - c_i v_{i+1}}{\tilde{d}_i}$$
$$= \frac{i}{i+1} (\tilde{f}_i + v_{i+1})$$

This can be optimized somewhat, which will be discussed in section III. Further details on the topics discussed in this section and on LU decomposition can be found in [2].

III. IMPLEMENTATION

The general Thomas algorithm is implemented directly in two C++ functions. The first is a function performing the forward substitution:

```
void general_forward(vec& a, vec& b, vec& c, vec& b_twiddle, int N)
{
  double decomp_factor = 0;
  //forward loop
  for (int i = 1; i<N; ++i){
    decomp_factor = a[i-1]/b[i-1];  // precalculate to get 5N FLOPS
    b[i] = b[i] - c[i-1]*decomp_factor;
    b_twiddle[i] = b_twiddle[i] - b_twiddle[i-1]*decomp_factor;
  }
}
```

Followed by a function performing the backwards substitution:

```
void general_backward(vec& b, vec& b_twiddle, vec& c, vec& u, int N)
{
  //setting first element
  u[N-1] = b_twiddle[N-1]/b[N-1];

  //backward loop
  for (int i = N-1; i>=1;--i){
    u[i-1] = (b_twiddle[i-1] - c[i-1]*u[i])/b[i-1];
  }
}
```

The vectors `a`, `b` and `c` store the lower, middle, and upper diagonals of the Toeplitz matrix respectivly. `b_twiddle` is the solution vector to the vector equation from which the algorithm is derived, `u` is the unknown vector we are solving for, and `N` is the dimension of the Toeplitz matrix. The forward substitiution, as first presented, requires $6(N-1) \approx 6N$ floating point operations (FLOPs) to complete. In "`general_forward`", the factor a_{i-1}/b_{i-1} is precalculated each iteration, thus reducing the number of FLOPs to $5(N-1) \approx 5N$. The backward substitution requires $3(N-1)+1 = 3N$ FLOPs to complete, thus the general algorithm requires $8N$ FLOPs to complete fully.

During forward substitution, the vector `b` is overwritten with the resulting $\tilde{d}_i$ values, since there is no dependency on previous diagonal elements. Vector `b_twiddle` is similarly overwritten with the resulting $\tilde{f}_i$ values. This, combined with passing the vectors by reference, reduces the amount of allocated memory by $2N \cdot 64$ bits for a total of $5N \cdot 64$ bits of memory used by the general algorithm.

The specialized Thomas algorithm is similarly implemented in two functions. The forward substitution:

```
void special_forward(vec& b_recip, vec& b_twiddle, int N)
{
  //forward loop
  for (int i = 1; i<N; ++i){
    b_twiddle[i] = b_twiddle[i] + b_twiddle[i-1]*b_recip[i-1];
  }
}
```

The backwards substitution:

```
void special_backward(vec& b_recip, vec& b_twiddle, vec& u, int N)
{
  //setting first element
  u[N-1] = b_twiddle[N-1]/b_recip[N-1];

  //backward loop
  for (int i = N-1; i>=1; --i){
    u[i-1] = (b_twiddle[i-1] + u[i])*b_recip[i-1];
  }
}
```

For the specialized algorithm, the reciprocals of the new diagonal elements are precalculated as:

$$\frac{1}{\tilde{d}_i} = \frac{i}{i+1} \text{ for } i = 1, 2, 3, ...N,$$

and passed to `"special_forward"` and `"special_backward"`, by reference, as the vector `b_recip`. This precalculation takes $2N$ FLOPs. The forward substitution takes $2(N-1) \approx 2N$ FLOPs. The backwards substitution takes $2(N-1)+1 = 2N$ FLOPs. As such, the specialized implementation takes a total of $6N$ FLOPs. During forward substitution, vector `b_twiddle` is overwritten with the resulting $\tilde{f}_i$ values. The total memory allocated by the specialized algorithm is $3N \cdot 64$ bits.

The LU decomposition was implemented using the Armadillo library's built in functions:

```
// LU decomposition with armadillo
lu(L,U,A);

// Solving resulting equation sets
vec y = solve(L,b_twiddle);
vec u = solve(U,y);
```

The matrices `L`, `U`, `A` store the lower triangular, upper triangular, and toeplitz matrix respectivly. The vector `y` contains the solution to

$$\mathbf{L}\mathbf{y} = \tilde{\mathbf{b}},$$

and the vector `u` contains the unknown values once the LU decomposition is complete. The computational cost of LU decomposition is on the order of $\frac{2}{3}N^3$ FLOPs [3]. The LU decomposition requires the allocation of three $N \times N$ matrices, and thus the memory needed for the matrices alone is $3N^2 \cdot 64$ bits.

Our implementation runs all the solvers sequentally. Each solver only allocates the memory it needs to perform its algorithm, and writes the results to binary files, before deallocating memory. Each solver performs an internal benchmark of its algorithm. The benchmark of the specialized Thomas algorithm includes time spent precalculating the $1/\tilde{d}_i$ values.

The entire C++ program runs the three solvers for one value of N. The Python-script `"data_analysis.py"` builds (if necessary) and runs the C++ program for given values of N. The Python-script then reads in the data from the binary files, and takes care of plotting and error analysis. For a more detailed explanation, and complete set of source code, see the repository linked in appendix A. For the specifications of the benchmark system, see appendix B.

IV. ANALYSIS

A. Plots of the general Thomas algorithm

We ran the Thomas algorithm with $N = 10$, $N = 10^2$, and $N = 10^3$ steps and created plots of the resulting data, and compared this with the analytic solution. These plots can be found in figures 1, 2 and 3.

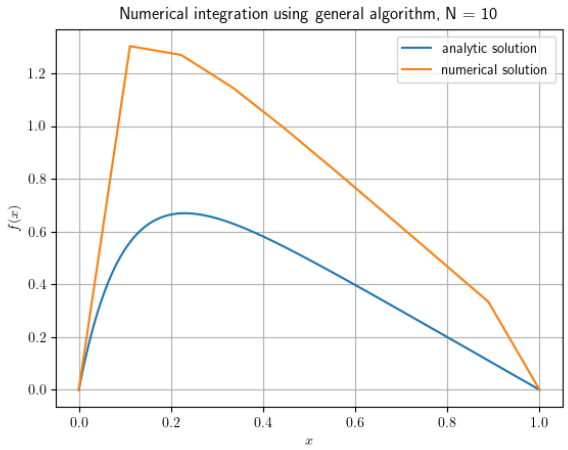

Figure 1. Plot of numerical and analytical solution, using the general Thomas algorithm with $N = 10^1$.

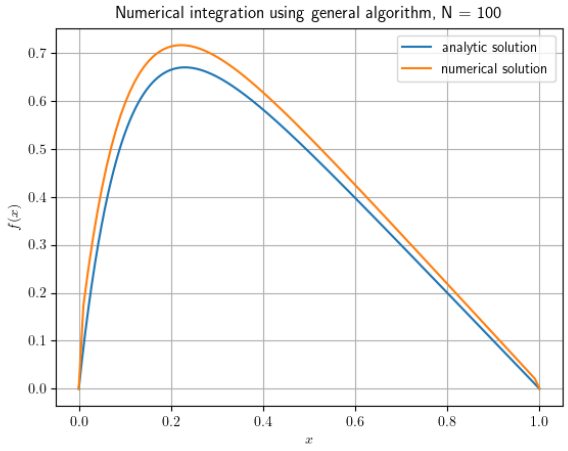

Figure 2. Plot of numerical and analytical solution, using the general Thomas algorithm with $N = 10^2$.

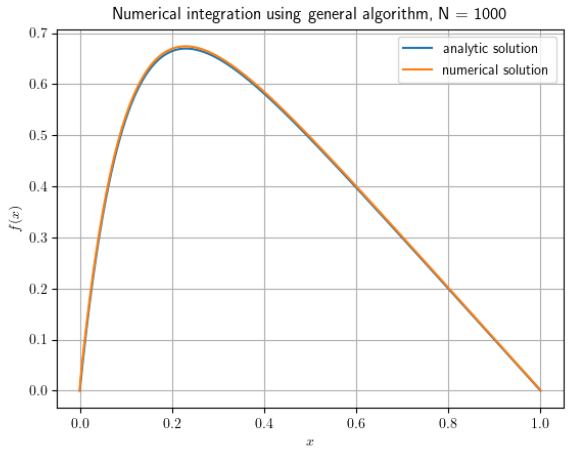

Figure 3. Plot of numerical and analytical solution, using the general Thomas algorithm with $N = 10^3$.

As expected we see that for larger N (shorter step length) the numerical approximation is closer to the analytic one, which also suggests that the algorithm is working as intended.

B. Relative errors

We measured the logarithm with base 10 of the maximum relative error for each algorithm for several N, and recorded the results in table I. The variable ϵ in this table was calculated using the following formula:

$$\epsilon = \max\left\{\log_{10}\left(\left|\frac{v_i - u_i}{u_i}\right|\right)\right\},$$

and as such it represents the maximum relative error in a single run of an algorithm.

We see in general that the error decreases for larger N with all algorithms. Notably, we have that the maximum relative error using LU decomposition is the same as the error using the general Thomas algorithm. Most likely there is some kind of optimization at work in the Armadillo package behind the scenes that causes it to work similarly to the general Thomas algorithm. We can also see that the special Thomas algorithm in general has a larger error than the other two algorithms, albeit not by much. The steady decrease in error indicates that we have not encountered machine precision as an issue with $N \leq 10^8$. However, for $N = 10^6$ and $N = 10^7$ in table I. the ϵ of the general algorithm did not decrease by one order of magnitude. Instead it remains at an order of 10^{-6}. For $N = 10^8$, the ϵ switches sign, as the relative error becomes less than 1. This apparent stagnation, followed by a sharp decrease in error, could indicate instability caused by loss of numerical precision. However, it could also be a property of the general algorithm. Verifying if the relative error has become unstable would require running the general Thomas algorithm for even larger N. This is something we do not have the memory for, and it is therefore left as an exercise for future research.

Table I. Table with $\log_{10}$ of relative error for general and special Thomas algorithms, LU decomposition, and $\log_{10}$ of step size h. To run the LU decomposition with $N \geq 10^5$ would have required more memory than we have available, and have thus not been performed.

$\log_{10}(h)$:	ϵ General	ϵ Special	ϵ LU	N
−1.041 39	$3.026\,20 \times 10^{-1}$	$3.601\,31 \times 10^{-1}$	3.0262×10^{-1}	10^1
−2.004 32	$3.426\,30 \times 10^{-2}$	$4.249\,89 \times 10^{-2}$	3.4263×10^{-2}	10^2
−3.000 43	$3.474\,75 \times 10^{-3}$	$4.338\,59 \times 10^{-3}$	3.4748×10^{-3}	10^3
−4.000 04	$3.479\,72 \times 10^{-4}$	$4.347\,83 \times 10^{-4}$	3.4797×10^{-4}	10^4
−5.000 00	$3.480\,18 \times 10^{-5}$	$4.348\,76 \times 10^{-5}$	-	10^5
−6.000 00	$4.210\,13 \times 10^{-6}$	$4.348\,75 \times 10^{-6}$	-	10^6
−7.000 00	$1.005\,17 \times 10^{-6}$	$4.343\,97 \times 10^{-7}$	-	10^7
−8.000 00	$-1.140\,50 \times 10^{-3}$	$3.765\,30 \times 10^{-8}$	-	10^8

C. Benchmarks

We measured execution time for the three algorithms (for various amounts of steps), in order to compare the time spent by each to see if everything behaves as expected. The results are shown in table II. We expected that the the slowest of the three would be the LU decomposisition, as that is a method used to solve general matrix-vector equations (something of the order $\frac{2}{3}N^3$ FLOPs needed). The general Thomas algorithm should be quicker, as that is dependent on the matrix being tridiagonal ($8N$ FLOPs), and the special Thomas algorithm should be the fastest of the three, as it is reliant on the elements also having specific values ($6N$ FLOPs). We can see from the execution times listed in table II that these expectations were met. The LU decomposition is the slowest, the general Thomas algorithm is quicker, and the special Thomas algorithm is the quickest one, for all amounts of steps used. Note that for $N = 10$ the execution time for the specialized and general algorithm is the same, which is also the same as the execution time for the specialized algorithm with $N = 10^2$ steps. This probably has something to do with precision in the measurement of the execution time, and seems to suggest that $1 \times 10^{-6}\,s$ is the shortest time interval we can measure, as the special algorithm should be faster with $N = 10$ steps than with $N = 10^2$ steps (for obvious reasons).

Table II. Table of execution time in seconds for general and special Thomas algorithms, and LU decomposition.

Algorithm	Execution time $[s]$	N
General Thomas	1×10^{-6}	10^1
General Thomas	3×10^{-6}	10^2
General Thomas	1.8×10^{-5}	10^3
General Thomas	0.000 119	10^4
Specialized Thomas	1×10^{-6}	10^1
Specialized Thomas	1×10^{-6}	10^2
Specialized Thomas	7×10^{-6}	10^3
Specialized Thomas	4.6×10^{-5}	10^4
LU decomposition	0.000 309	10^1
LU decomposition	0.000 755	10^2
LU decomposition	0.171 256	10^3
LU decomposition	158.701	10^4

V. CONCLUSION

In this report we have derived, implemented and compared three different numerical algorithms to solve Poisson's equation set up as a matrix-vector problem. As such we have familiarized ourselves with and presented some numerical linear algebra methods. We have worked with the Thomas algorithm [1], a specialized version of said algorithm for our problem (see section II for further details), and LU decomposition (see [3] for details). The source term from the Poisson's equation was chosen to be one with an analytic solution, so that we can calculate the maximum relative error in the numerical solutions. We also measured the execution time of all three algorithms, and these three things together allowed us to compare the algorithms with each other quantitavely.

We ran the general Thomas algorithm for $N = 10$, $N = 10^2$ and $N = 10^3$ and plotted the numerical solution together with the analytic solution. The plots are shown in figures 1, 2 and 3. In general we see that the numerical solution gets closer to the analytic solution for larger N, which indicates that the algorithm is working correctly.

The execution times measured showed that the LU decomposition was slower than the general Thomas algorithm which again was slower than the specialized Thomas algorithm. The measured times are listed in table II. The general Thomas algorithm should use about $8N$ FLOPs, the specialized Thomas algorithm should use about $6N$ FLOPs, and the LU decomposition method should use about $\frac{2}{3}N^3$ FLOPs, so the results are as expected.

The errors also behaved largely as expected with them getting smaller for larger N, other than some small instability in the errors for the general Thomas algorithm. We were not able to, however, run at sufficiently large N in order to encounter any real issues from machine precision due to memory limitations. Interestingly enough, the error in the general Thomas algorithm is equal to that from the LU decomposition. This suggests that somewhere behind the scenes the Armadillo package does optimizations that render the processes very similar. We also noted that the error is slightly larger for the special Thomas algorithm than with the other two, but it is not so large as to be an immediate concern in employing the algorithm, but where more precision is needed the general Thomas algorithm or the LU decomposition would be better choices.

[1] L. Thomas, *Elliptic Problems in Linear Difference Equations over a Network*, Tech. Rep. (Watson Sc. Comp. Lab. Rep., Columbia University, New York, 1949).

[2] M. Hjorth-Jensen, *Computational Physics Lecture Notes Fall 2015* (Department of Physics, University of Oslo, Oslo, 2015).

[3] M. Hjorth-Jensen, *Computational Physics Lectures: Linear Algebra methods*, Tech. Rep. (Department of Physics, University of Oslo, Oslo, 2018).

Appendix A: Project files

All code for this report was written in C++ and Python 3.8, and the complete set of files can be found at https://github.com/FunkMarvel/FYS3150_Project_1.git in the `src` directory.

1. Source code

Here is a list of source code files used for this report.

a. `data_analysis.py`

Main script for running project, plotting and data analysis. https://github.com/FunkMarvel/FYS3150_Project_1/blob/master/src/data_analysis.py

b. `main.cpp`

Main cpp file for running algorithms. https://github.com/FunkMarvel/FYS3150_Project_1/blob/master/src/main.cpp

c. `general_main.cpp`

File for setting up and benchmarking general Thomas algorithm. https://github.com/FunkMarvel/FYS3150_Project_1/blob/master/src/general_main.cpp

d. `general_algorithm.cpp`

File containing the implementation of the general Thomas algorithm. https://github.com/FunkMarvel/FYS3150_Project_1/blob/master/src/general_algorithm.cpp

e. `special_main.cpp`

File for setting up and benchmarking specialized Thomas algorithm. https://github.com/FunkMarvel/FYS3150_Project_1/blob/master/src/special_main.cpp

f. `special_algorithm.cpp`

File containing the implementation of the specialized Thomas algorithm. https://github.com/FunkMarvel/FYS3150_Project_1/blob/master/src/special_algorithm.cpp

g. `LU_main.cpp`

File for setting up and benchmarking LU decomposition. https://github.com/FunkMarvel/FYS3150_Project_1/blob/master/src/LU_main.cpp

h. `relative_error.cpp`

C++ function calculating relative error. https://github.com/FunkMarvel/FYS3150_Project_1/blob/master/src/relative_error.cpp

2. Selected results

Here is a folder of selected results from running our code. The run used to generate this data is copied from terminal and pasted in this directory's readme-file. https://github.com/FunkMarvel/FYS3150_Project_1/tree/master/set_of_selected_data

Example plots can be found in doc/plots. https://github.com/FunkMarvel/FYS3150_Project_1/tree/master/doc/plots

Appendix B: System specifications

All results included in this report were achieved by running the implementation on the following system:

- CPU: AMD Ryzen 9 3900X
- RAM: $2 \times 8\,\text{GB}$ Corsair Vengeance LPX DDR4 3200 MHz