# Implementation and Test of Numerical Optimization Algorithms in $\mathrm{C} / \mathrm{C}++$ 

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## Summary (English)

The goal of this report is to describe the twice continuously differentiable unconstrained optimization problem. Recognizing that it is impossible to check every point, it provides the mathematical foundation for the BFGS algorithm, to solve the problem locally.

Once this is introduced, the report moves on to a practical implementation the steps required to begin using scientific computing by including BLAS and LAPACK. It then provides the documentation for the implementation in C and an example of how to use it.

Then, it describes how the optimization algorithms can be called from $\mathrm{C}, \mathrm{C}++$, Objective-C++, and FORTRAN.

Finally, it does some performance tests, and it is found that libopti is fast compared to scripting based solutions, and as much as 7-8 times faster than the GNU Scientific Library, however it is also not entirely reliable for solving every problem in its class. In fact, no implementation is tested which could solve every problem in its class.

## Summary (Danish)

Målet for denne afhandling er at beskrive dobbelt-differentiable, ikke begrænsede optimeringsproblemer. Det indses, at det er umuligt at gennems $\emptyset$ ge ethvert punkt, så der bruges en metode kaldet BFGS til at løse problemet lokalt.

Når dette er gjort, er det videre mål med afhandlingen at give en praktisk implementering. De trin der er nødvendige for at begynde på Scientific Computing ved at inkludere både BLAS og LAPACK. Derefter leveres dokumentation for implementeringen i C og instruktioner på, hvordan det bruges.

Dernæst beskrives hvordan implementeringen kan kaldes fra C, C ++ , ObjectiveC ++ og FORTRAN.

Til sidst udføres nogle tests. Målet er at vise, at libopti er en hurtig implementering i forhold til scripting-baserede metoder, og at den er hurtig nok til at kunne bruges i stedet for andre, lignende bibilioteker til C.

Desværre viser det sig, at algoritmen ikke altid er helt pålidelig, men det er der ingen af dem, der er.

## Preface

This thesis was prepared at the department of Informatics and Mathematical Modelling at the Technical University of Denmark in fulfilment of the requirements for acquiring an M.Sc. in Informatics.

Optimization is an ancient field of mathematics. It all started back in 300 B.C. when Euclid considered the minimal distance between two points. Since then, development was slow until the 17 th and 18th century. There Newton's Method was discovered.[oF12]

A pretty common theme among all the optimization algorithms is that, especially for large-dimensional problems, their solution time is very large.[JN00] Because of this, optimization as we know it today did not take off until the middle of the 20th century with the invention of computers usable for scientific computing.[oF12] Since then, many algorithms have appeared to solve various different problems.

The purpose of this project is to create an algorithm designed to solve a specific type of optimization problem using the C language on Linux systems.

C is a rather old programming language with a very powerful, free software compiler[Fou12] and long-standing support. The speed with which C code runs is very high, and so writing the project in C with POSIX subsystems has two main advantages:

- Fast calculation is achievable.
- The project can be built entirely upon free software, making it relatively
easy to port to many hardware architectures and making sure that users of the software do not face restrictions.

Optimization is an important tool in all manner of decision-making processes. It is important in physics, operations research, investments, and many other fields.[JN00]

An optimization problem consists of an objective function, which depends on a potentially large amount of variables, but gives a single output, alternatively with constraints. The goal is to find the minimum or maximum to the objective function within the constraints of the problem.

A problem with no constraints is called an unconstrained optimization problem. This software focuses specifically on this type of problem with an additional property: The objective must be twice continuously differentiable.

In other words, it will solve the problem:[JN00]

$$
\min _{x} f(x)
$$

Where $f(x) \in \mathcal{C}^{2}: \mathbb{R}^{n} \rightarrow \mathbb{R}$.

Contained within is a description of the algorithm and what it does, and from which sources it was derived. This is followed by an implementation guide and a guide to using the software in C. Several test cases of the software will be demonstrated and the performance will be measured compared to similar software.

The library will be using the ATLAS Basic Linear Algebra Subroutines[ABB $\left.{ }^{+} 99\right]$ for it's heavy-duty computations for performance benefits.

## Problem definition

- Provide a guide to using BLAS within GNU/Linux Ubuntu systems.
- Provide a usable implementation of an optimization algorithm for twice continuously differentiable unconstrained problems.
- Provide documentation for the function, as well as any other function in use, unless such is already provided elsewhere.
- Provide a guide on how to include and use them in your project.
- Provide a way to use the library functions within other languages.

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Many of the algorithms and methods explored in the project have been provided professor Hans Bruun Nielsen at IMM DTU, whom I would like to thank. He wrote the IMM Optibox library for MATLAB, upon which several of the included algorithms are based.

Large parts of the algorithms are based upon the work done by NetLib with their package BLAS, without which most of this work would have taken significantly longer, and the algorithms would have been significantly slower.

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## CHAPTER 1

## Theory of Unconstrained Optimization

The goal of solving any unconstrained minimization problem is to get the values of $x$ for which[JN00]:

$$
\min _{x} f(x)
$$

Where $f(x) \in \mathcal{C}^{2}: \mathbb{R}^{n} \rightarrow \mathbb{R}$.
The goal of any unconstrained maximization problem is to get the values of $x$ for which

$$
\max _{x} f(x) \Rightarrow \min _{x}-f(x)
$$

Where $f(x) \in \mathcal{C}^{2}: \mathbb{R}^{n} \rightarrow \mathbb{R}$.
This simplifies the entire process as we no longer have to consider the maximization problem.

This value of the vector x at which it obtains the properties needed to fulfil the objective is denoted $x^{*}$.

A point $x^{*}$ is a global minimizer if and only if

$$
f\left(x^{*}\right) \leq f(x) \quad \forall x \in \mathbb{R}^{n}
$$

The global minimizer can be difficult to find, because the function $f(x)$ may not be known analytically and can only be sampled. Since $f(x)$ spans over at least one real line, there is at least one uncountably infinite amount of points to consider[Han08]. Thus it is impossible to visit every location.

However, because the function is twice continuously differentiable, any one point, and in particular it's derivatives, have a lot to say about the surrounding area on the function.[Sch07]

Thus it is far more feasible, for this type of problem, to consider minimizing more locally.

A point $x^{*}$ is a local minimizer if there is an open set $\mathcal{S}$ containing

$$
x^{*}, \text { such that } f\left(x^{*}\right) \leq f(x) \quad \forall x \in \mathcal{S}
$$

### 1.1 Optimality Conditions

An immediate question which arises when asked to find a global or even local minimizer, is one of how to check whether you are in one. It is, as previously discussed, infeasible to check every point. In fact, even the open set in an uncountably infinite set is itself uncountable.[Kre89]

To get started, Taylor's Theorem must be invoked[JN00].

Suppose that $f \in \mathcal{C}^{1}: \mathbb{R}^{n} \rightarrow \mathbb{R}$, that $\alpha \in \mathbb{R}$ and that $p \in \mathbb{R}^{n}$. Then:

$$
\begin{equation*}
f(x+p)=f(x)+\nabla f(x+\alpha p) p \tag{1.1}
\end{equation*}
$$

for some $\alpha \in[0,1]$.
Furthermore, if $f$ is twice continuously differentiable:

$$
\begin{array}{r}
\nabla f(x+p)=\nabla f(x)+\int_{0}^{1} \nabla^{2} f(x+\alpha p) p d t \\
f(x+p)=f(x)+\nabla f(x) p+\frac{1}{2} p \nabla^{2} f(x+\alpha p) p \tag{1.3}
\end{array}
$$

From this, one can derive the First-Order Optimality Condition[JN00]:

If $x^{*}$ is a local minimizer and $f \in \mathcal{C}^{1}$ at and near said local minimizer, then $\nabla f\left(x^{*}\right)=0$

And the Second-Order Sufficient Optimality Condition[JN00]:

If $x^{*}$ is a local minimizer of $f$ and $\nabla^{2} f$ exists and is continuous in an open neighbourhood of $x^{*}$, then $\nabla f\left(x^{*}\right)=0$ and $\nabla^{2} f\left(x^{*}\right)$ is positive definite.

The algorithm which will be written does not test for the Second-order optimality condition. It is quite work-intensive to check, because it involves lots of determinant calculations for use in Sylvester's Criterion[Mey00]. On top of that, other conditions can ensure that this condition is fulfilled most of the time[JN00]. On top of that, the search direction algorithm which will be used assumes that $\nabla^{2} f(x)$ is indeed positive definite for any $x$ visited. More on this later.

In practice, the imprecision of the data types available on a computer means that the first order optimality condition is actually very rarely achievable, due to cumulative rounding errors in the calculations.

So, rather than finding the exact point, the algorithm will stop once it is "close enough" or have done an unreasonable number of calculations. What "close enough" and "unreasonable" exactly means can be specified by the user.

There are several methods of finding out if the first order optimality condition is almost fulfilled[JN00]:

- $\left\|\nabla f\left(x^{k}\right)\right\| \leq \varepsilon_{1}$
- $\left\|x^{k+1}-x^{k}\right\| \leq \varepsilon_{2}$
- $f\left(x^{k}\right)-f\left(x^{k+1}\right) \leq \varepsilon_{3}$
- $k>k_{\max }$ or neval $>$ neval $_{\max }$ aka. the "give up" condition.

Where neval is the number of function evaluations and $k$ is the number of steps taken already. Now that we know when we land on a minimizer, it is necessary to find out how to best arrive to the minimizer.

### 1.2 Finding the minimizer

As mentioned earlier, an optimization problem on the real numbers has an infinite number of points to check, but it is only feasible to visit a finite amount of points. Thus, an algorithm that only visits a finite number of points is needed, and it needs to start somewhere.

That "somewhere" is defined by the user and is called $x^{0}$. The goal is to go through a series of steps whereby an $x^{k}, k=1 . . N$ for each iteration is attained until we reach $x^{*}$, the desired minimizer. This process is performed by finding a step, also known as a descent direction, $p^{k}$ by:

$$
\begin{equation*}
x^{k+1}=x^{k}+\alpha^{k} p^{k} \tag{1.4}
\end{equation*}
$$

where $\alpha^{k}$ is the step-length. More on step-lengths later. For now, assume that $\alpha^{k}=1$.

Step $p^{k}$ is an $n$-dimensional vector which is quite well named: It is the direction and magnitude which, if one is to take a step towards $p^{k}$ using the current iterate, there is good reason to believe that the function value will decrease.


Figure 1.1: $p^{0}$ to $p^{2}$ on Himmelblau

Perhaps the most important search direction is found using a process called Newton's Method, which results in a Newton direction[JN00]. This direction is derived from the second-order Taylor series approximation:

$$
\begin{equation*}
f\left(x^{k}+p^{k}\right) \approx f+p^{k} \nabla f\left(x^{k}+p^{k}\right)+\frac{1}{2} p^{k} \nabla^{2} f\left(x^{k}+p^{k}\right) p^{k}:=m\left(p^{k}\right) \tag{1.5}
\end{equation*}
$$

Assuming that $\nabla^{2} f^{k}$ is positive definite, you can simply set $\nabla m^{k}\left(p^{k}\right)=0$ and solve for $p^{k}$. This gives:

$$
\begin{equation*}
p^{k}=-\frac{\nabla f^{k}}{\nabla^{2} f^{k}} \tag{1.6}
\end{equation*}
$$

Thus each update will result in a step such as this one:

$$
\begin{equation*}
x^{k+1}=x^{k}-\alpha^{k} \frac{\nabla f^{k}}{\nabla^{2} f^{k}} \tag{1.7}
\end{equation*}
$$

Thus, so far the algorithm looks like this:

1. Begin with a starting guess $x^{0}$ on the at least locally convex function $f \in \mathcal{C}^{2}: \mathbb{R}^{n} \rightarrow \mathbb{R}$ where $n$ is the number of input dimensions in the function.
2. Sample the function value $f\left(x^{0}\right)$, the gradient $\nabla f\left(x^{0}\right)$ and the Hessian $\nabla^{2} f\left(x^{0}\right)$
3. While the first order optimality conditions are not yet met:
(a) Find $p^{k}=-\frac{\nabla f\left(x^{k}\right)}{\nabla^{2} f\left(x^{k}\right)}$
(b) Use some kind of line-search technique, one is described later, to find a value $\alpha^{k}$ which satisfies the line-search conditions.
(c) Take the step: $x^{k+1}=x^{k}+\alpha^{k} p^{k}$
(d) Increment $k$.
(e) Sample the function value $f\left(x^{k}\right)$, the gradient $\nabla f\left(x^{k}\right)$ and the Hes$\operatorname{sian} \nabla^{2} f\left(x^{k}\right)$

### 1.3 Line-search

Once a descent direction $p^{k}$ has been found by using, for example, Newton's method, it should be decided how far to go in this descent direction, henceforth referred to as line-search. This is specifically because when the descent direction was determined we only had local information about the function, and, when taking the full step, it is actually possible that the cost at the new point is larger than the one at the old point[JN00].

Defining a new function, where $\alpha$ is the search length given at the iteration $k$, which can be put in place of $\alpha^{k}$ we get:

$$
\begin{equation*}
\varphi(\alpha)=f\left(x^{k}+\alpha p^{k}\right) \tag{1.8}
\end{equation*}
$$

The derivation of how to get the Newton step was explained in the previous chapter, and it assumed that the step-length $\alpha^{k}=1$ was used. This is a good place to start the search[HBN10].

First it is important to look at the slope of $\varphi(\alpha)$. Basic vector calculus[HEJK06] immediately reveals the following:

The slope of the function $\varphi(\alpha)$ can be found as:

$$
\begin{equation*}
\frac{d \varphi}{d \alpha}=\frac{\partial f}{\partial x_{1}} \frac{d x_{1}}{d \alpha}+\frac{\partial f}{\partial x_{2}} \frac{d x_{2}}{d \alpha}+\ldots+\frac{\partial f}{\partial x_{n}} \frac{d x_{n}}{d \alpha}<0 \tag{1.9}
\end{equation*}
$$

Which is also known as:

$$
\begin{equation*}
\frac{d \varphi}{d \alpha}=p^{k} \nabla f\left(x^{k}+\alpha p^{k}\right)<0 \tag{1.10}
\end{equation*}
$$

As a result of this, if $\alpha$ is small, we are almost guaranteed to get a satisfying point[HBN10]. However, when taking the actual step, the step will also be small, leading to a slower approach to the minimizer with far more calculations necessary.

The aim of line-search is to find a value of $\alpha$ such that we get a useful decrease in the value of the original function. In soft line-search we are satisfied with a region in which this is true and are willing to pick any point within this region. The interval in which it does so can be defined by the following conditions, known as the Wolfe-conditions[JN00]:

$$
\begin{align*}
\varphi(\alpha) & \leq \varphi(0)+c_{1} \frac{d \varphi(0)}{d \alpha}  \tag{1.11}\\
\frac{d \varphi(\alpha)}{d \alpha} & \geq c_{2} \frac{d \varphi(0)}{d \alpha} \tag{1.12}
\end{align*}
$$

Where $0<c_{1}<0.5$ and $c_{1}<c_{2}<1$. Usually, $c_{1}$ is chosen small and $c_{2}$ is chosen very large. Typical values could be: $c_{1}=10^{-4}, c_{2}=0.9$.

The first condition, also known as the Armijo rule, ensures that the function value has decreased enough for the new choice of $\alpha$ to make the step "worth it".

The second condition, known as the curvature condition, ensures that the slope at the new point has been reduced sufficiently. This hopes to ensure that the next iteration does not start from an area with a very steep slope, which could otherwise cause the iteration sequence to shoot very far off the target.

The following image displays a rough estimate of an example of what acceptable ranges could be a soft line-search algorithm. The thick black marker indicates acceptable ranges.


Figure 1.2: Example of line-search acceptable ranges

A possible algorithm to do this would be[HBN10]:

1. $\alpha:=0, k:=0$. If $\frac{d \varphi(0)}{d \alpha} \geq 0$, stop immediately - 1 st order necessary conditions were already met or the step $p$ was not determined correctly.
2. Define $\alpha_{\max }$ so be a user-specified maximum line-search length, and $k_{\max }$ to be the largest amount of iterations tolerable.
3. $a:=0, b:=\min \left(1, \alpha_{\max }\right)$.
4. While $k<k_{\max }$
(a) Increment $k$.
(b) If $\varphi(\alpha)<\varphi(0)+c_{1} \frac{d \varphi(0)}{d \alpha}$, set $a=b$.
i. If $\frac{d \varphi(b)}{d \alpha}<c_{2} \frac{d \varphi(0)}{d \alpha}$, set $b=\min \left(2 b, \alpha_{\max }\right)$.
ii. Otherwise, terminate the while lop.
(c) If the above was not true, check if $a=0$ and $\frac{d \varphi(b)}{d \alpha}<0$. If it is, set $b=b / 10$.
(d) In all other cases, exit the while loop.
5. Set $\alpha=b$ and terminate the algorithm entirely if: $(a>0$ and curvature condition is fulfilled) or ( $b \geq \alpha_{\max }$ and the curvature condition is not fulfilled).
6. While $k<k_{\max }$
(a) Increment $k$.
(b) Refine $\alpha, a, b$ using a following method.
(c) Exit this loop immediately if the Wolfe conditions are satisfied.
7. If, in spite of everything, the new location still has a higher function value, set $\alpha=0$.

A possible refinement method is to create a parabola with similar characteristics and finding the minimum value of it, such as this one:

$$
\psi(t)=\varphi(a)+\frac{d \varphi(a)}{d \alpha}(t-a)+c(t-a)^{2}
$$

Where $c=\frac{\varphi(b)-\varphi(a)-(b-a) \frac{d \varphi(a)}{d \alpha}}{(b-a)^{2}}$. A possible way to do this is with the following algorithm[HBN10]:

1. $D:=b-a . c:=\frac{\varphi(b)-\varphi(a)-D \frac{d \varphi(a)}{d \alpha}}{D^{2}}$.
2. If $c>0$, set $\alpha=\frac{a-\frac{d \varphi(a)}{d \alpha}}{2 c}$, because the parabola is a "frown". $\alpha=\min (\max (\alpha, a+0.1 D), b-0.1 D))$ to ensure no divergence.
3. Otherwise, set $\alpha=(a+b) / 2$.
4. If the armijo-condition is satisfied by this $\alpha$, set $a=\alpha$, otherwise set $b=\alpha$. Return $a$ and $b$.

Another method entirely is to use exact line-search, which is designed to result in a step-length close to a value of $\alpha$ such that $\varphi(\alpha)$ is minimized. The algorithm to do this is similar to soft line-search, but the main differences are that, in the first loop, $a$ is only updated when (but before) $b$ is. In addition, the condition for stopping the final loop in that algorithm is changed to:

$$
\left(\left|\frac{d \varphi(\alpha)}{d \alpha}\right| \leq \tau\left|\frac{d \varphi(0)}{d \alpha}\right|\right) \text { or }(b-a \leq \varepsilon)
$$

The good thing about this approach is that, in theory, it should result in the following relation (on successful runs, it approximately does):

$$
\begin{equation*}
\nabla f\left(x^{k}+\alpha p^{k}\right) \perp p^{k} \tag{1.13}
\end{equation*}
$$

The bad thing about it is that it takes much longer to compute it, and thus it has fallen out of favour in recent years[HBN10].

### 1.4 Using a trust region with line search

It is also possible to combine some of the methods of the line search and trust region methods. A trust region $\mathcal{T}$ is defined as such:[HBN10]

$$
\begin{equation*}
\mathcal{T}=\{h \mid\|h\| \leq \Delta\}, \quad \Delta>0 \tag{1.14}
\end{equation*}
$$

The goal here is to adjust $\Delta$ in such a way that it represents a "trust-worthy" spherical area with the radius $\Delta$, in order to reduce the computation time of the line search method.

One way to do this is to first normalize the step if the step is too long. Once this is done, a normal line search, as described above, is performed. The line search gives a step length $\alpha$ which tells how far it was deemed beneficial to in the direction of the normalized step.

- If less than the full step was taken, $\alpha<1$, reduce the trust region by $\rho_{1}$.
- If the slope was too steep at the final point of the line search, the trust region may be too small. Increase it by a factor of $\rho_{2}$.
- At the end of each iteration, make sure that the trust region is larger than the stopping criteria for too small step length.

Where $0<\rho_{1}<1$ and $\rho_{2}>1$.
By doing this, the step from each iteration is fitted into a trust region. The better the steps have been in the past, the larger steps we take, and vice versa, which can save computation time for each iteration's line search.

### 1.5 Quasi-Newton BFGS method

A quasi-newton optimization method is a method which uses iterates to arrive at a minimal function value in similar vein to the steepest descent method or

Newton's method for optimization[JN00].
The problem with Newton's method when used for optimization is that it requires the Hessian of the function that is to be optimized. The Hessian of such a function can be extremely difficult to compute and may consist of unreasonably long expressions that require a lot of computer operations to calculate explicitly, let alone find. The idea of a Quasi-Newton method is to approximate the Hessian well enough to be able to use what is essentially Newton's Method without requiring the user to explicitly supply the Hessian.[JN00]

One of these is the BFGS method, named after Broyden, Fletcher, Goldfarb, and Shanno who invented it.

To derive it, we can start with the quadratic model of the objective function at the current iterate $x_{k}$ [JN00]

$$
\begin{equation*}
m_{k}\left(p^{k}\right)=f^{k}+\nabla f^{k} p^{k}+\frac{1}{2} p^{k} B^{k} p^{k} \tag{1.15}
\end{equation*}
$$

Where $B^{k}$ is a positive definite approximation that is updated at every iteration $k$. The minimizer of the above model can be written as:

$$
\begin{equation*}
p^{k}=-\left(B^{k}\right)^{-1} \nabla f^{k} \tag{1.16}
\end{equation*}
$$

Instead of computing $B^{k}$ at every iteration, Davidson proposed updating it using the next iterate $x^{k+1}$ using the following quadratic model[JN00]:

$$
\begin{equation*}
m_{k+1}\left(p^{k}\right)=f^{k+1}+\nabla f^{k+1} p^{k}+\frac{1}{2} p^{k} B^{k+1} p^{k} \tag{1.17}
\end{equation*}
$$

We require of of $B^{k+1}$, based on the Wolfe conditions used for line-searching, that:

$$
\begin{equation*}
\nabla m_{k+1}\left(p^{k}\right)=\nabla f^{k+1}-\alpha^{k} B^{k+1} p^{k}=\nabla f^{k} \tag{1.18}
\end{equation*}
$$

By rearrangement we get:

$$
\begin{equation*}
\alpha^{k} B^{k+1} \alpha^{k} p^{k}=\nabla f^{k+1}-\nabla f^{k} \tag{1.19}
\end{equation*}
$$

This is known as the secant equation. At this point, to simply the notation, the following vectors are defined:

$$
\begin{equation*}
h^{k}=\alpha^{k} p^{k}, \quad y^{k}=\nabla f^{k+1}-\nabla f^{k} \tag{1.20}
\end{equation*}
$$

Thus the secant equation becomes, with the second version being particularly important for BFGS:

$$
\begin{equation*}
B^{k+1} h^{k}=y^{k} \Leftrightarrow H^{k+1} y^{k}=h^{k} \tag{1.21}
\end{equation*}
$$

Where $H^{k}=\frac{1}{B^{k}}$.
The secant equation requires that $H^{k+1}$ maps $y^{k}$ into $h^{k}$. For this to be possible, they must satisfy the curvature condition:

$$
\begin{equation*}
h^{k} y^{k}>0 \tag{1.22}
\end{equation*}
$$

In order to make sure that this condition is fulfilled, it needs to be enforced. By imposing the restrictions on the line search mentioned in the previous chapter, the curvature condition is guaranteed to hold[JN00] becauseof the curvature condition imposed as part of the Wolfe Conditions:

$$
\begin{equation*}
y^{k} h^{k} \geq\left(c_{2}-1\right) \alpha^{k} \nabla f^{k} p^{k} \tag{1.23}
\end{equation*}
$$

This admits for a number of different solutions. In order to choose a specific unique solution, an additional condition of closeness is specified. Denoting the new iterate simply $H$, we want the new iterate to be positive definite and symmetric, and we want the minimal distince between the two, so the following optimization problem is solved.

$$
\min _{H}\left\|H-H^{k}\right\|
$$

subject to

$$
H=H^{T}, \quad H y^{k}=s^{k}
$$

This problem has the unique solution which is precisely the BFGS updating method[JN00]:

$$
\begin{equation*}
H^{k+1}=\left(I-\frac{1}{y^{k} h^{k}} h^{k} y^{k}\right) H^{k}\left(I-\frac{1}{y^{k} h^{k}} y^{k} h^{k}\right)+\frac{1}{y^{k} h^{k}} h^{k} h^{k} \tag{1.24}
\end{equation*}
$$

The only remaining problem is figuring out where to start. Since this is only an update formula - what does it update from the first time?

There appears to be no "magic trick" for this, but starting with an evaluation of the true $H_{0}$ would work well. However, there is a useful heuristic which is to take a steepest descent direction for the first step and, afterwards, set [JN00]:

$$
\begin{equation*}
H^{0}=\frac{y^{k} h^{k}}{y^{k} y^{k}} I \tag{1.25}
\end{equation*}
$$

Thus, the entire algorithm is now:

1. Begin with a starting guess $x^{0}$ on the at least locally convex function $f \in \mathcal{C}^{2}: \mathbb{R}^{n} \rightarrow \mathbb{R}$ where $n$ is the number of input dimensions in the function.
2. Set $H^{0}=I$.
3. Sample the function value $f\left(x^{0}\right)$, the gradient $\nabla f\left(x^{0}\right)$.
4. While the first order optimality conditions are not yet met:
(a) Find $p^{k}=-\frac{\nabla f\left(x^{k}\right)}{\nabla^{2} f\left(x^{k}\right)}$
(b) Use the line search technique to find a value $\alpha^{k}$ which satisfies the line-search conditions.
(c) Take the step: $x^{k+1}=x^{k}+\alpha^{k} p^{k}$
(d) Define $h^{k}$ and $y^{k}$ in accordance with (19). Check the secant equation.
(e) Compute $H^{k+1}$ in accordance with (24). If this is the first iteration, use (25).
(f) Increment $k$.
(g) Sample the function value $f\left(x^{k}\right)$, the gradient $\nabla f\left(x^{k}\right)$.

A final thing that is very important to note: As this algorithm updates the inverse Hessian, that means it is no longer needed to solve a linear system. Instead, a simple multiplication of a matrix and a vector is all that is needed. This is huge for computer performance.[Mey00][Net12][ABB ${ }^{+99]}$

### 1.6 Finite Difference

In many cases even differentiating a function once, let alone twice, can sometimes be difficult, even if it can be proven that the function in question is continuously differentiable. A forward differentiation method is included and can be used. Forward difference approximation is just the definition of derivative without taking the limit as $h$ approaches 0 . Rather, $h$ is set to a specific, small value, which causes an error of size $O(h)$ [Sch07].

$$
\begin{equation*}
f^{\prime}(x)=\frac{f(x+h)-f(x)}{h}+O(h) \tag{1.26}
\end{equation*}
$$

It should be noted that setting $h$ to a negative number immediately causes backwards difference approximation.

$$
\begin{equation*}
f^{\prime}(x)=\frac{f(x+h)-f(x)}{h}+O(h) \tag{1.27}
\end{equation*}
$$

The overall result of using both a Quasi-Newton method as well as finite difference is that only the function $f$ itself needs to be given explicitly, although it is still required that $f \in \mathcal{C}^{2}$. This can lead to very large reductions in the work required by the user.

## Chapter 2

## Installing BLAS and LAPACK in Ubuntu

Switching gears to the more practical implementation, it will be necessary to install BLAS in order to use the optimization toolbox, because the optimization toolbox is written using BLAS libraries for multiplications involving vectors and matrices.

This guide and software is written for use primarily with Ubuntu 12.04 (but it should work on many POSIX-complient systems), and will take you step-by-step to getting the solution running on your system. If you are not using Ubuntu, the setup steps may differ.

### 2.1 Installing Eclipse, BLAS \& LAPACK

This guide assumes we are using Ubuntu. We are going to be using ATLAS, which is a mostly hardware-independant and very efficient variety of the BLAS and (some of the) LAPACK packages. However it does not implement all LAPACK functions, so LAPACK is installed separately.[Net12]

We also need a good IDE, like Eclipse. Alternatively, it is possible to use a text
editor such as gedit, VIM or emacs. For Eclipse+ATLAS, open a terminal and execute:

```
1 apt-get install eclipse-cdt libatlas-dev liblapack-dev build-essential
```



Figure 2.1: Installing Eclipse, GCC, BLAS, LAPACK

Wait for Ubuntu's package manager to finish the process. Once it is finished, you may close the terminal. Eclipse for C, a C compiler, BLAS and LAPACK are now installed.

### 2.2 Creating a new project

1. This is only relevant if you use Eclipse.
2. Go into File -> New -> C project.
3. Type in a project name, and select Empty Project. Select the toolchain Linux GCC. Then press Finish.


Figure 2.2: Creating a new project in Eclipse-cdt
4. Now you should include a new file. Go into File -> New -> Source File
5. Call the file main.c, as the tool-chain will always attempt to compile this file at first.

### 2.3 Importing, using linking BLAS \& LAPACK

In order to include BLAS, simply type \#include <cblas.h> in the preamble of whichever file you need it in. Then open the project properties.


Figure 2.3: Accessing Project Properties

Expand GCC Build, then click on Settings. In the new selection panel under Tool Settings, go into the GCC linker and select Libraries, and add the libraries "m", "lapack" and "blas" without the quotes. Do not add any Library Paths. In order to use the library tests, also include rt.h. On Mac OS X, add Accelerate.framework.


Figure 2.4: Linking the compiler to BLAS and LAPACK

The equivalent can be performed by calling "gcc main.c -O3 -o blastest.out -lblas -llapack -lm" in the terminal without the quotes.

### 2.4 First Matrix-multiplications

### 2.4.1 Matrix-Vector

In order to perform a Matrix-Matrix multiplication, I need to use the blas library. For this purpose, the cblas.h library is used. Column Major order is preferred since this saves computer resources, given that the functions I are using were written in FORTRAN, and thus the matrices use FORTRAN order, or Column Major.

All of the functions have logical names to them: Generally, they take a form starting with the name of the library, then underscore, ending with the function name as explained on netlib.[Net12] They are put into 3 categories: vectorvector operations are level 1, matrix-vector operations are level 2, matrix-matrix operations are level 3 .

In order to do a matrix-vector multiplication, which is a level 2 subroutine, something like this

```
1 cblas_dgemv(CblasColMajor, CblasNoTrans, A m, A n, alpha, A, A n, x, numcols x
    , beta, y, numcols y);
```

It will perform the following operation:

$$
y=\alpha \cdot A \cdot x+\beta \cdot y
$$

Here is an example of using it:

```
//Some actual BLAS-testing!
int M1row = 3;
double M1[] = {
        3, 1, 3,
        1, 5, 9,
        2, 6, 5
}; //Remember it's transposed!
double x[] = {-1, -1, 1};
double y[3] = {0.0};
cblas_dgemv(CblasColMajor, CblasNoTrans, 3, 3, 1.0, M1, 3, x, 1, 0.0, y,
    1); //matrix-vector mult
//y = alpha*A*x + beta*y
int i; //Print result
for (i=0; i<3; ++i) printf("%5.3f\n", y[i]);;
```

It gives the result:

```
-2.000
0.000
-7.000
```


### 2.4.2 Matrix-Matrix

A level 3 function will generally perform the following operation:

$$
y=\alpha \cdot A \cdot B+\beta \cdot y
$$

And so the input format I use for the general case is:

```
1 cblas_dgemm(CblasColMajor, CblasNoTrans, CblasNoTrans, A[m], A[n], alpha, A,
    numcols A, B, numcols B, beta, y, cols of output);
```

Here is an example:

```
int main()
{
    int M1row = 3;
    double M1[] = {
                3, 1, 3,
                    1, 5, 9,
                2, 6, 5
    }; //Remember it's transposed!
    int M2col = 3;
    double M2[] = {
                1, 2, 3,
            4, 5, 6,
            7, 8, 9
    }; //Remember it's transposed!
    double y[3] = {0.0};
    int M3row = 3;
    double matrixout[9] = {0.0};
    cblas_dgemm(CblasColMajor, CblasNoTrans, CblasNoTrans, 3, 3, 3, 1.0, M1,
            M1row, M2, M2col, 0.0, matrixout, M3row); //matrix-matrix mult
    int i;
    for (i=0; i<3; ++i) printf("%5.3f\n", y[i]);;
    printf("\n");
```

Produces the following output:

```
11.000 29.000 36.000
29.000 65.000 87.000
47.000 101.000 138.000
```

Which is as expected.

### 2.5 Solving your first LA-equations

Despite the fact that the BFGS method does not need any LAPACK routines at all, working with LAPACK is still useful for further functions in the toolbox in the future.

Since there seems to be no decent, complete C wrapper for LAPACK for Linux, we'll just have to do it ourselves! Using the LAPACK documentation[ABB $\left.{ }^{+} 99\right]$. Before the main method, or in a separate file, you must import the proper functions into C .

Since I link to LAPACK, I can use the methods directly. There are a few things to keep in mind. In C, any FORTRAN77 function I import is appended with an underscore. This happens due to the way a FORTRAN77 library is compiled.[Lin12] Looking at the documentation I can see that dgtsv can do what I want. Here is an example of importing such a function into a more usable C format:

```
1 static long dgtsv(long N, long NRHS, double *DL, double *D, double *DU, double
    *B, long LDB)
    {
    extern void dgtsv_(const long *Np, const long *NRHSp, double *DL, double *
            D, double *DU, double *B, const long *LDBp, long *INFOp);
        long info;
        dgtsv_(&N, &NRHS, DL, D, DU, B, &LDB, &info);
        return info;
    }
```

This function will solve a system of linear equations in which only the diagonal, upper diagonal and lower diagonal are defined. Everything else is set to 0. Let us try to solve the system:

$$
\left(\begin{array}{lll}
3 & 6 & 0 \\
6 & 1 & 4 \\
0 & 4 & 3
\end{array}\right)\left(\begin{array}{l}
x_{1} \\
x_{2} \\
x_{3}
\end{array}\right)=\left(\begin{array}{c}
-1 \\
3 \\
-3
\end{array}\right)
$$

Here is an example of using it:

```
double z[] = { -1, 3, -3 };
int info, j;
double l[] = {6, 4};
double u[] = {6, 4};
```

```
double d[] = {3, 1, 3};
info = dgtsv(3, 1, l, d, u, z, 3);
if (info != 0) printf("Failure with error: %d\n", info);
for (j=0; j<3; ++j) printf("%5.3f\n", z[j]);
```

It returns:

```
0.769
-0.551
-0.265
```

Next I wish to take a look at Cholesky factorization. Looking at the documentation, there is dpbtrf, which is Cholesky Factorization which takes the matrix as the first column, then the lower diagonal part of the second column, append with 0 's to make the column as long as the first one, then the lower diagonal part of the next column, append with 0 's and so on, which can be imported as such:

```
static long dpbtrf(char UPLO, long N, long KD, double* AB, long LDAB)
{
    extern void dpbtrf_(char* UPLOp, long* Np, long* KDp, double* AB, long*
        LDABp, long* infop);
    long info;
    dpbtrf_(&UPLO, &N, &KD, AB, &LDAB, &info);
    return info;
}
```

Let's say I wish to find the lower matrix such that $L^{T} L=A$ for the positive definite symmetric matrix

$$
A=\left(\begin{array}{ccc}
4 & -2 & -6 \\
-2 & 10 & 9 \\
-6 & 9 & 14
\end{array}\right)
$$

Then this is what I would do:

```
double m[] = {4, -2, -6, 10, 9, 0, 14, 0, 0};
info = dpbtrf('L', 3, 2, m, 3);
if (info != 0) printf("Failure with error: %d\n", info);
for (i=0; i<3; ++i)
{
        for (j=0; j<3; ++j)
            if (j > i)
                printf(" %5.3f", 0.0f);
            else
                printf(" %5.3f", m[j*3+(i-j)]); //FORTRAN order...
        printf("\n");
}
```

This will return the correct result:

```
2.000 0.000 0.000
    -1.000 3.000 0.000
    -3.000 2.000 1.000
```

Now that the system is set up, the real work can begin.

## CHAPTER 3

## Library documentation

## ucminf

Finds the minimizer to an unconstrained optimization problem given by fun() by using the Quasi-Newton BFGS method. Extra parameters may be sent using the void structure.

Call:

```
1 int opti_ucminf(void (*fun) (double *x, double *f, double *g, void *p), double *x, int \(n\), double *opts, double *D, int *evalused, double * perfinfo, double *xiter, void *p);
```

Input:

- fun - A function handle to a function with the structure:
- *x - The address of an array of doubles representing the point to take the function at.
- *f - The address of the storage of the function evaluation
- ${ }^{*} \mathrm{~g}$ - The address of an array of doubles. Will be filled with the derivative of $f(x)$.
$-{ }^{*} \mathrm{p}-\mathrm{A}$ pointer to a void structure that can be anything.
- *x - The starting guess x for the function. On exit, the optimal value for x .
- n - Number of variables given to the function
- *opts - An array containing:
- delta - Initial value for largest stepsize used by the linesearching.
- tolg - The value which the norm of g is under when the 1st order KKT conditions are met.
- tolx - If the stepsize is less than tolx* (tolx $+\operatorname{norm}(\mathrm{x}, \mathrm{n}, 2)$ ), stop.
- maxeval - The maximum number of tolerable iterations before stopping.
- findiffh - Used in the finite difference approximation for fun(). If set to $0, \mathrm{~g}$ is expected. Warning: Using findiffh $=0$ and not supplying g in fun WILL result in errors.
- Default: 1, 1e-4, 1e-8, 100, 0
- *D - An array containing an initial estimation of the inverse Hessian to the function. Set to NULL to start with with I. On exit, a pointer to the Hessian. Warning: Points to unclaimed memory if *D was set to NULL on exit!
- *evalused - A pointer to an integer which will be filled with the number of evaluations. Warning: NOT ITERATIONS.
- *perfinfo - A pointer that must point to an array of doubles of size $6^{*}$ maxeval. Will contain performance information which can be printed using printperf.
- *xiter - If null, nothing happens. Otherwise, contains a sequence of $x$ for each iteration on exit. Must be preallocated to size $n^{*}$ maxiter (default n*100)
- *p - A void-pointer which can contain anything. Is passed through the function and all the way over to fun().
- -1 - memory allocation, error
- 0 - perfect starting guess, success
- 1 - Stepsize H became NaN, inf or -inf, error
- 2 - Stopped due to small derivative g, success
- 3 - Stopped due to small change in x , success
- 4 - Norm of stepsize became 0 , success.
- 5-Too many function evaluations, potential failure

Example usage:

```
//Requires C99 at least
//Standard ANSI C libraries for I/O
#include <stdio.h>
#include <stdlib.h>
#include <stddef.h>
//Include the library itself
#include <libopti.h>
#include <math.h>
void himmelblau(double* x, double* f, double* df, void *p)
{
        *f = pow(x[0]*x[0] + x[1] - 11,2) + pow(x[0] + x[1]*x[1] - 7,2);
        df[0] = 2*(2*x[0]*(x[0]*x[0] + x[1] - 11) + x[0] + x[1]*x[1] - 7);
        df[1] = 2*(-11+x[0]*x[0] + x[1] + 2*x[1]*(-7 + x[0] + x[1]*x[1]));
        return;
}
int main()
{
        //Number of inputs to n, number of max iterations
        const int maxiters = 100;
        int n = 2;
        double x[2] = {1, 1};
        double perfinfo[maxiters*6];
        double xinfo[n*maxiters];
        double opts[] = {1.0, 0.00000001, 0.00000001, maxiters, 0};
        int ucminfr = opti_ucminf(himmelblau, x, n, opts, NULL, NULL, perfinfo,
            xinfo, NULL);
        int folderinfo = opti_printperf_tofolder(perfinfo, xinfo, maxiters, n, "
            testhimmelblau");
        printf("%i\n",ucminfr);
        printf("(%f, %f)\n",x[0], x[1]);
        return 0;
}
```

Resulted in:

```
1 Beale test function:
2 Solve time: 0.000046
3 Save to folder info: 0
4 Solution return: 2
```

In other words, the program was minimized in 0.000046 seconds, and the algorithm stopped due to small size of derivative.

## line search

Calculates a step length of a step on a function, and updatex $x, f, g$. Can save return performance information about the line search. Also takes options.

Call:

```
1 int opti_linesearch(void (*fun)(double *x, double *f, double *g, void *p),
    double *x, int n, double *f, double *g, double *h, double *opts, double
        *perf, void *p);
```

Input:

- fun - A function handle to a function with the structure:
- $*_{\mathrm{x}}$ - The address of an array of doubles representing the point to take the function at.
- *f - The address of the storage of the function evaluation
- ${ }^{*} \mathrm{~g}$ - The address of an array of doubles. Will be filled with the derivative of $f(x)$.
$-{ }^{*} \mathrm{p}-\mathrm{A}$ pointer to a void structure that can be anything.
- *x - Pointer to the variables given to the function
- n - Number of variables given to the function
- $*_{f}$ - The address of the storage of the function evaluation
- ${ }^{\mathrm{g}}$ - The address of an array of doubles. Will be filled with the derivative of $f(x)$.
- *h - The search direction, the steplength multiplier,
- *opts- An array with a few options:
- choice: $1=$ soft linesearch, $0=$ exact linesearch
- cp1: Constant 1 timed onto derivative of f at initial point (not used if choice $=0$ )
- cp2: Constant 2 timed onto derivative of $f$ at initial point
- maxeval:Maximum number of evaluation before quitting.
- amax: Maximum tolerable search direction multiplier
- Default: 0 , 1e-3, 1e-3, 10, 10. Giving NULL to opts will load these values.
- *perf- Some simple performance information from linesearch. Contains: search direction multiplier, final slope, number of evaluations
- *p - A pointer to a void structure that can be anything.

Returns:

- 0 - Successful return
- -1 - Dynamic memory allocation failed.
- $1-\mathrm{h}$ is not downhill or it is so large and, maxeval so small, that a better point was not found.

Example call: Used internally by ucminf. See appendix A.10.

## interpolate

Finds the minimizer of a 1D parabola which is given by two points $a$ and $b$.

```
1 double opti_interpolate(double *xfd, int n);
```

Input:

- $\operatorname{xfd}-\mathrm{An}$ array consisting of $\mathrm{xfd}=\mathrm{a}, \mathrm{b}, \mathrm{f}(\mathrm{a}), \mathrm{f}(\mathrm{b}), \mathrm{f}^{\prime}(\mathrm{a})$. The function value at $a$ and the function value at $b$. The derivative of the function value at a.
- n - The dimension of the problem original problem within which the parabola is to be constructed.

Output: The minimizer of the parabola.

Example call: See appendix A.6. Line search uses it for refining the interval.

## findiff

Finds $f$ and $g$ directly if $h==0$. Otherwise, approximates $g$ with forward difference approximation using an $\mathrm{O}(\mathrm{n}+1)$ algorithm. If h is negative, uses backward difference.

Call:

1 int opti_findiff(void (*fun) (double *x, double *f, double *g, void *p), double *x, int $n$, double *f, double *g, double h, void *p);

Input:

- fun - A function handle to a function with the structure:
- *x - The address of an array of doubles representing the point to take the function at.
- *f - The address of the storage of the function evaluation
- ${ }^{*} \mathrm{~g}$ - The address of an array of doubles. Will be filled with the derivative of $f(x)$.
- *p - A pointer to a void structure that can be anything.
- ${ }^{x}$ - Pointer to the variables given to the function
- n - Number of variables given to the function
- $*_{\mathrm{f}}$ - The address of the storage of the function evaluation
- ${ }^{\mathrm{g}}$ - The address of an array of doubles. Will be filled with the derivative of $f(x)$.
- h - The stepsize of the forward approximation. Can be any real number. If $h$ is $0, g$ is expected to be handed directly.
- ${ }^{\mathrm{p}}$ - A pointer to a void structure that can be anything.


## Returns:

- 0 - Successfully returned the function and its derivative.
- -1 - Dynamic memory allocation failed.


## printperf tofile

Prints performance information to a file in such a way that the file has the iterations listed among the columns:

- Number of evaluations of $f$ done in the iteration.
- The value of f at the iteration
- The norm of the derivative of the function at the iteration
- The linesearch limit delta at the value of the iteration
- The scaling factor for the step as given by the linesearch
- The slope of the function at the point in the direction of the step

Call:

```
1 int opti_printperf_tofile(double* perf, int maxiters, char* filename);
```

Input:

- *perf - The performance array given by ucminf
- maxiters - The maximum allowed iterations. Must be the same number passed to opts. Set to negative number to defeault to 100 .
- filename - A string containing the filename.

Returns:

- 0 - Successfully saved the data to file.
- -2 - Failed to open/write file. Nothing is saved.


## printperf_tofolder

Prints performance information to a specified folder at the location the program is run. Makes 7 subfiles named:

- evals.txt - Number of evaluations of $f$ done in the iteration.
- fun.txt - The value of $f$ at the iteration
- ng.txt - The norm of the derivative of the function at the iteration
- delta.txt - The linesearch limit delta at the value of the iteration
- am.txt - The scaling factor for the step as given by the linesearch
- finalslope.txt - The slope of the function at the point in the direction of the step
- x.txt - The contents of x at each iteration

Call:

1 int opti_printperf_tofolder(double* perf, double* xiter, int maxiters, int $n$, char* foldername);

Input:

- *perf - The performance array given by ucminf
- maxiters - The maximum allowed iterations. Must be the same number passed to opts. Set to negative number to defeault to 100 .
- foldername - A string containing the foldername from the location your program is run.

Returns:

- 0 - Successfully saved the data to file.
- -2 - Failed to open/write file. Nothing is saved.
- -3 - File existed with name of folder to be created. Nothing saved.
- -4 - Folder could not be created. Check permissions or drive


### 3.1 Usage example

In this example we seek to solve the famous Rosenbrock problem[Ros60].
The Rosenbrock Function is a non-convex function invented by Howard H. Rosenbrock in 1960. It has a long, narrow parabolic-shaped valley with only a single minimum. To find the valley is easy, but to find the minimum is quite difficult.

$$
\begin{equation*}
f(x)=\left(1-x_{1}\right)^{2}+100\left(x_{2}-x_{1}^{2}\right)^{2} \tag{3.1}
\end{equation*}
$$

In order to do this, the library needs to be added onto the system. The compiled form of the library is called libopti.so.

If the library is not already compiled, a makefile is provided inside the Release folder of the project folder which compiles it. It is required that ATLAS and GCC is installed for this to work. This will build the shared object libopti.so.

To include the object in your own program, GCC must be told to link with it, and where the object is.

- If the object is in /usr/bin/ or /usr/local/bin then GCC only needs to be told that the library should be added using the -lopti argument.
- If the object elsewhere, GCC also needs to be told where the library is located. In addition to the above, use the -L/path/name/to/library argument.

Next, the header file of the library needs to be included in your project. This is done by adding the line, assuming libopti.h is in the same folder as your code.

```
1 #include "libopti.h"
```

If libopti.h is in /usr/include or /usr/local/include, you can type:

```
1 #include <libopti.h>
```

in the file. Afterwards, the library can be freely used, such as with this example minimizing the Rosenbrock function.

```
//Requires C99 at least
//Standard ANSI C libraries for I/O
#include <stdio.h>
#include <stdlib.h>
#include <stddef.h>
//Include the library itself
#include <libopti.h>
#include <math.h>
void rosenbrock(double* x, double* f, double* df, void *p)
{
    *f = pow(1 - x[0],2) + 100*pow(x[1] - x[0]*x[0],2);
    df[0] = -2 + 2*x[0] - 400*(x[1] - x[0]*x[0])*x[0];
    df[1] = 200*x[1] - 200*x[0]*x[0];
    return;
}
int main()
{
    //Number of inputs to n, number of max iterations
    int n = 2;
    double x[2] = {4, 2};
    double opts[] = {1.0, 0.0001, 0.00000001, 100, 0};
    int ucminfr = opti_ucminf(rosenbrock, x, n, opts, NULL, NULL, NULL, NULL,
        NULL);
    printf("%i\n",ucminfr);
    printf("(%f, %f)\n",x[0], x[1]);
    return 0;
}
```

Resulting in the following output when run:

[^0]
## Chapter 4

## Mixing FORTRAN and C

It may also be useful to be able to run the library from multiple different programming languages. Therefore, it is going to be essential to be able to run this library from multiple different languages.

Since C++ and Objective C are supersets of C, the ability to call any C function within them is given for free.

However, FORTRAN needs to implemented explicitly.
On the next page is a comparison between the different datatypes in FORTRAN and C, respectively.[Lin12]

A subroutine in FORTRAN is basically the same a function call in C, but it doesn't have a return type, which in C can be represented as the return type void. All FORTRAN functions have their input arguments passed by reference. In other words, we must give it an address which points to the location of our variable rather than the variable itself.

It is important to remember that arrays already get passed by reference to C programs, and as a result it is not necessary to use the address-of symbol when working with arrays.

| byte | unsigned char |
| :---: | :---: |
| integer*2 | short |
| integer | long |
| integer A(m,n) | int A(n,m) |
| logical | int |
| real | float |
| real*8 | double |
| real*16 | real*16 |
| complex z | structfloat realnum; float imagnum; z; |
| double complex z | structdouble realnum; double imagnum; z; |
| character | char |
| character $\operatorname{str}(\mathrm{m})$ | char* str[m] |

Table 4.1: Table of data types in FORTRAN and C

In addition, all subroutine names must be written in lower case letters because a compiled FORTRAN program contains only lowercase letters as they are all converted. In addition, it will append an underscore at the end of the function name.[Lin12]

This means that these two function calls are equivalent:

CALL MMADD (A, B, m, n)
and
mmadd_(A, B, \&m, \&n);

And finally, C arrays are in row major, FORTRAN arrays are in column major. This means that for example the following array:[Lin12]
double $A[2][3]=\{\{a, b, c\},\{d, e, f\}\} ;$

Which can be interpreted as a flat array, is read by C programs like this:

$$
\left(\begin{array}{lll}
a & b & c \\
d & e & f
\end{array}\right)
$$

But writing the basically equivalent statement in FORTRAN sees it like this:

$$
\left(\begin{array}{ll}
a & d \\
b & e \\
c & f
\end{array}\right)
$$

To call a function from C there are a set of things that need to be done.

Make sure the correct software installed. For this, built-essential and fort77 are vital. They can be installed in Ubuntu with:

```
1 sudo apt-get install build-essential fort77.
```

Write the function. This will assume general knowledge of FORTRAN 77. Perhaps the function is already written. The function must have the inputs specified by the relevant optimization procedure. Remember that everything is passed to FORTRAN subroutines by reference, so normal header declarations will ensure compliance with the requirement for pointers.

Compile the subroutines(s) into a library using the following command, making sure you are in the same directory you saved the compiled file(s):

```
1 f77 -c filename.F
```

Generate a library file by collecting all the subroutines in a single file. To do this, type the following command, remaining in the same folder:

```
1 ar rcv libmylib.a *.o
```

Generate an overview of the included subroutines with the following command:

```
1 ranlib libmylib.a
```

Over in C, add a new library: mylib (The name of the library file created minus the lib in front and the appended .a) Next, add a library search path which is exactly the path where you saved the library.

Create a C wrapper for the function and make it return the whichever type you wish by defining e.g. (Addition of two matrices $A^{m \times n}$ and $B^{m \times n}$ ):

```
static void mmadd(double* a, double* b, long m, long n)
{
    extern void mmadd_(double* a, double* b, long* mp, long* np);
    mmadd_(a, b, &m, &n);
    return;
}
```


## Chapter 5

## Using the library in

This library also comes with bindings for several popular languages. Using the knowledge given above about how to work with FORTRAN and C together, the below lists documentation and examples of how to use it.

### 5.1 FORTRAN

It should be noted that while it is possible to code problems in FORTRAN and import those into C, and then use libopti to optimize, the reverse is not possible up until FORTRAN 2003. Since FORTRAN 2003 was not in the discussion above and very few people use the newer versions of FORTRAN, this problem is placed outside the scope of this report.

However, it is still possible to perform an optimization as part of a MATLAB program, and this is how.

Given the project is set up in C as explained in section 5 , the following can be done.

Make an example of Rosenbrock coded in FORTRAN with the appropriate header for use with the UCMINF method.

```
    SUBROUTINE ROSENBROCKF(X, F, DF)
c ==============PARAMETERS===============
c Scalar arguments:
    INTEGER N
    DOUBLE PRECISION X(N), F, DF(N)
c Written by: Christian Wichmann Moesgaard
c This FORTRAN77 program is specifically for demonstration purposes.
c This implements the Rosenbrock function and is used for an example
c demonstrating how to optimize FORTRAN functions with the optimization
c toolbox.
    N = 2
    F}=(1-X(1))**2+100*(x(2)-x(1)**2)**
    DF(1) = -2 + 2*X(1) - 400*(X(2)-X(1)**2)*X(1)
    DF(2) = 200*X(2) - 200*(X(1))**2
    RETURN
    END
```

Then, compile the subroutine as demonstrated in chapter 6.1 and include it, then create the following wrapper function in the C program:

```
void rosenbrockf(double* x, double* f, double* df)
{
    extern void rosenbrockf_(double* x, double* f, double* df);
    rosenbrockf_(x, f, df);
}
```

And finally the minimum may be found using the same method as in section 5, replacing rosenbrock inside the ucminf call with rosenbrockf.

Doing the above should correctly return the result $x \approx(1,1)$.

Furthermore, it is possible to make this function return something back to FORTRAN. The general idea here is to:

1. Program a FORTRAN model
2. Compile it, then load it into C as above.
3. Use it in a C function which takes the inputs as desired and compile it, remembering to respect the rules for interoperability.
4. Use this function in FORTRAN.

For example, to optimize the above subroutine, one could do the following:

```
//Requires C99 at least
//Standard ANSI C libraries for I/O
#include <stdio.h>
#include <stdlib.h>
#include <stddef.h>
//Include the library itself
#include <libopti.h>
#include <math.h>
void rosenbrockf(double* x, double* f, double* df)
{
    extern void rosenbrockf_(double* x, double* f, double* df);
    rosenbrockf_(x, f, df);
}
void optirosenbrock_(double *x, double *np)
{
    int n = *np;
    double opts[] = {1.0, 0.0001, 0.00000001, 100, 0};
    opti_ucminf(rosenbrock, x, n, opts, NULL, NULL, NULL, NULL, NULL);
}
```

Compiling this function, the Rosenbrock function, which was originally written in FORTRAN, can now be optimized by libopti and the optimized values can be returned back to FORTRAN again using the following:

```
SUBROUTINE OPTIMBROCK(X, F, DF)
C ==============PARAMETERS================
c Scalar arguments:
    INTEGER N
    DOUBLE PRECISION X(N), F, DF(N)
    N = 2
    X(1) = 3
    X(2)=2
    CALL OPTIROSENBROCK(X, N)
    CALL ROSENBROCKF (X, F, DF)
    RETURN
    END
```


### 5.2 Mac OS X and iOS

The library is already built with OS X in mind, and will correctly attempt to use Accelerate instead of ATLAS. The test-cases will use MACH functions instead of POSIX functions where appropriate.

The library can be fully compiled as part of an Objective C application. This is because Objective C is an extension of C.[Inc12a]

This also implies that the library works on an iPhone or iPad, since it uses Apple's built-in Accelerate framework, which is available since iOS 4.0.[Inc12b]

Here is an image of an iPad Simulator having correctly solved a 20 -variable Ackley optimization problem from psuedo-random numbers between -3 and 3 (more on the Ackley optimization problem in the next chapter):


Figure 5.1: Solution to Ackley problem on iPad

## Chapter 6

## Performance testing

For the performance testing, 6 different functions have been selected. They were all found on the the webpage: [Hed12a] Except Himmelblau, which was acquired through CampusNet. All of these functions are problems of the form:

$$
\min _{x} f(x)
$$

Where $f(x) \in \mathcal{C}^{2}: \mathbb{R}^{n} \rightarrow \mathbb{R}$.

These 6 functions will be run through 4 different and common optimization software packages as well as my own. These software packages are:

1. IMM Optibox UCMINF, latest version*
2. Maple 16 Optimization Toolbox using a the function "NLPSolve" internal to the Optimization Assistant, latest version*
3. MATLAB's Optimization Toolbox using FMINUNC, latest version*
4. minlbfgs for $\mathrm{C}++$ version 2.6.0
*as of this writing.

Each problem will be run 10 times and the average time will be calculated, except in cases where the computation time is so long that it is inconceivable that this algorithm will win out.

The performance of these software packages will be compared with the performance of the version of UCMINF made alongside this report, and their computation time will be measured in real time (seconds) on the following set-up:

- Intel Core i7-950 @ 3.07 GHz (4 cores, hyperthreading)
- 8GB PC3-12800 CL9 RAM
- Ubuntu 12.1064 -bit
- Using ATLAS, GCC 4.6.3, Optimize level 3

However, before one even gets to that, there's an important thing to note about licensing.

1. IMM Optibox is developed internally at DTU and is, as such, accessible to projects within DTU. However, it builds upon MATLAB, which is an expensive piece of proprietary software. The source code is readily visible. The dependence on MATLAB means that it is using a scripting language and thus cannot be used in embedded devices due to restrictions. The software does run on GNU Octave, but issues arise with porting to iOS or Android or similar.
2. The Maple 16 optimization algorithms are proprietary, and build upon the proprietary piece of software, Maple. The same problems apply as with MATLAB.
3. MATLAB's Optimization Toolbox is proprietary software built for proprietary MATLAB. It features DRM and is, like MATLAB, not suitable for embedded devices.
4. minlbfgs is free software, but it is also copyleft under the GNU GPLv2. It does offer dual licensing, though, but that is expensive.[ALG12a]

This is worth keeping in mind before even looking at performance comparisons between libopti and the other solutions.

### 6.1 Himmelblau

The first problem that will be looked at is Himmelblau's function. This problem is famous for its relative simplicity, making it easy to understand for students. However, the 1st and especially 2nd hand derivatives become somewhat complicated. It is named after David Mautner Himmelblau who introduced it in 1972.[Him72]

$$
\begin{equation*}
f(x)=\left(x_{1}^{2}+x_{2}-11\right)^{2}+\left(x_{1}+x_{2}^{2}-7\right)^{2} \tag{6.1}
\end{equation*}
$$

Here is a plot of the relevant area of the function:


Figure 6.1: 4 global minima at $x \approx\{(3,2),(-2.8,3.1),(-3.8,-3.3),(3.6,-1.8)\}$


Figure 6.2: libopti's path

First, a comparison of the CPU times, where the starting guess is $(1,1)$ and the algorithm converges towards the minimum at $(3,2)$. All times are measured in seconds.

| Attempt | UCMINF | FMINUNC | Maple 16 | minlbfgs | libopti |
| ---: | :---: | :---: | :---: | :---: | :---: |
| 1 | 0.0121 | 0.0114 | 0.0314 | 0.000029 | 0.000072 |
| 2 | 0.0097 | 0.0126 | 0.0302 | 0.000007 | 0.000010 |
| 3 | 0.0076 | 0.0138 | 0.0296 | 0.000004 | 0.000009 |
| 4 | 0.0096 | 0.0135 | 0.0296 | 0.000004 | 0.000009 |
| 5 | 0.0075 | 0.0116 | 0.0296 | 0.000004 | 0.000009 |
| 6 | 0.0096 | 0.0135 | 0.0296 | 0.000004 | 0.000009 |
| 7 | 0.0075 | 0.0131 | 0.0296 | 0.000006 | 0.000009 |
| 8 | 0.0096 | 0.0132 | 0.0296 | 0.000006 | 0.000009 |
| 9 | 0.0077 | 0.0112 | 0.0296 | 0.000007 | 0.000009 |
| 10 | 0.0099 | 0.0144 | 0.0296 | 0.000007 | 0.000009 |
| Average | 0.0091 | 0.0128 | 0.0304 | 0.000008 | 0.000015 |

Table 6.1: Performance on Himmelblau


Figure 6.3: Average, methods are ordered in the same way as the table

The Maple and MATLAB solutions are completely out of the question. They are based on scripting languages. minlbfgs takes the lead here, but not particularly much. In fact, the difference was unnoticeable.

The code used to take these samples can be found in Appendix C.2.

### 6.2 Rosenbrock

The Rosenbrock Function is a non-convex function invented by Howard H. Rosenbrock in 1960. It has a long, narrow parabolic-shaped valley with only a single minimum. To find the valley is easy, but to find the minimum is quite difficult.[Ros60]

$$
\begin{equation*}
f(x)=\left(1-x_{1}\right)^{2}+100\left(x_{2}-x_{1}^{2}\right)^{2} \tag{6.2}
\end{equation*}
$$

Here is the relevant area of the function:


Figure 6.4: Minimum at $x=(1,1)$


Figure 6.5: libopti's path

First, a comparison of the CPU times, where the starting guess is $(3,3)$ and the algorithm converges towards the minimum at $(1,1)$. All times are measured in seconds.

| Attempt | UCMINF | FMINUNC | Maple 16 | minlbfgs | libopti |
| ---: | :---: | :---: | :---: | :---: | :---: |
| 1 | 0.0550 | 0.0462 | $0.004^{*}$ | 0.000046 | 0.000134 |
| 2 | 0.0318 | 0.0416 |  | 0.000022 | 0.000020 |
| 3 | 0.0262 | 0.0436 |  | 0.000020 | 0.000018 |
| 4 | 0.0242 | 0.0422 |  | 0.000026 | 0.000018 |
| 5 | 0.0263 | 0.0436 |  | 0.000034 | 0.000018 |
| 6 | 0.0243 | 0.0439 |  | 0.000025 | 0.000018 |
| 7 | 0.0262 | 0.0427 |  | 0.000020 | 0.000018 |
| 8 | 0.0244 | 0.0441 |  | 0.000020 | 0.000018 |
| 9 | 0.0264 | 0.0418 |  | 0.000020 | 0.000018 |
| 10 | 0.0263 | 0.0435 |  | 0.000020 | 0.000018 |
| Average | 0.0291 | 0.0370 | $<0.004$ | 0.000025 | 0.000030 |

Table 6.2: Performance on Rosenbrock, * = Maple could not measure lower time deltas


Figure 6.6: Average, methods are ordered in the same way as the table

The MATLAB solutions are completely out of the question. They are based on scripting languages. minlbfgs takes the lead here by quite a vast amount.

Something interesting happened here, however. libopti was faster in most cases, but in the first optimization it was so significantly slower that the entire average was shifted in favor of minlbfgs. These results persisted through multiple test-runs of the same code.

The code used to take these samples can be found in Appendix C.3.

### 6.3 Beale

The second problem is Beale's function. This problem was introduced by E. Beale in 1958 and is famous for having a minimum in an otherwise almost flat area surrounded by very steep "hills" all around the sides. This can prove tricky for functions who do not use line search or trust regions.[Bea58]

$$
\begin{equation*}
f(x)=\left(1.5-x_{1}\left(1-x_{2}\right)\right)^{2}+\left(2.25-x_{1}\left(1-x_{2}\right)^{2}\right)^{2}+\left(2.625-x_{1}\left(1-x_{2}\right)^{3}\right)^{2} \tag{6.3}
\end{equation*}
$$

Here is a plot of the relevant area of the function:


Figure 6.7: Minimum at $x=(3,0.5)$


Figure 6.8: libopti's path

First, a comparison of the CPU times, where the starting guess is $(4,2)$ and the algorithm converges towards the minimum at $(3,0.5)$. All times are measured in seconds.

| Attempt | UCMINF | FMINUNC | Maple 16 | minlbfgs | libopti |
| ---: | :---: | :---: | :---: | :---: | :---: |
| 1 | 0.0199 | 0.0392 | 0.012001 | 0.000060 | 0.000076 |
| 2 | 0.0206 | 0.0258 | $0.004^{*}$ | 0.000024 | 0.000017 |
| 3 | 0.0230 | 0.0269 |  | 0.000021 | 0.000017 |
| 4 | 0.0207 | 0.0250 |  | 0.000021 | 0.000017 |
| 5 | 0.0203 | 0.0270 |  | 0.000021 | 0.000016 |
| 6 | 0.0205 | 0.0250 |  | 0.000021 | 0.000017 |
| 7 | 0.0224 | 0.0271 |  | 0.000021 | 0.000017 |
| 8 | 0.0209 | 0.0270 |  | 0.000021 | 0.000016 |
| 9 | 0.0270 | 0.0241 |  | 0.000021 | 0.000017 |
| 10 | 0.0215 | 0.0271 |  | 0.000020 | 0.000017 |
| Average | 0.0217 | 0.0301 | 0.004800 | 0.000025 | 0.000023 |

Table 6.3: Performance on Beale, ${ }^{*}=$ Maple could not measure lower time deltas


Figure 6.9: Average, methods are ordered in the same way as the table

Once again we see the scripting based solutions fall significantly behind. In this case, interestingly, Maple also does quite well. However, Maple does not give precise enough time measurements once again. This time, like with Rosenbrock, libopti was slowest on the first attempt, but in this case it was fast enough for the other attempts to slightly win out on the average of 10 runs.

All algorithms converged towards the minimum.

The code used to take these samples can be found in Appendix C.4.

### 6.4 Easom

The third problem is Easom's function. This problem was introduced by E. Easom in 1990 and has a characteristic where it is very flat, except just around its one and only minimum at $(\pi, \pi)$, where it falls very sharply. This problem is hard to solve with poor computer precision as the algorithm may stop due to due to its first order conditions.[Eas90]

$$
\begin{equation*}
f(x)=-\cos \left(x_{1}\right) \cos \left(x_{2}\right) \mathrm{e}^{-\left(x_{1}-\pi\right)^{2}-\left(x_{2}-\pi\right)^{2}} \tag{6.4}
\end{equation*}
$$

Here is a plot of the relevant area of the function:


Figure 6.10: Minimum at $x=(\pi, \pi)$


Figure 6.11: libopti's path

First, a comparison of the CPU times, where the starting guess is $(4,2)$ and the algorithm converges towards the minimum at $(3,0.5)$. All times are measured in seconds.

| Attempt | UCMINF | FMINUNC | Maple 16 | minlbfgs | libopti |
| ---: | :---: | :---: | :---: | :---: | :---: |
| 1 | 0.0160 | 0.0190 |  |  | 0.000689 |
| 2 | 0.0058 | 0.0212 |  |  | 0.000595 |
| 3 | 0.0057 | 0.0196 |  |  | 0.000593 |
| 4 | 0.0077 | 0.0202 |  |  | 0.000592 |
| 5 | 0.0058 | 0.0194 |  |  | 0.000613 |
| 6 | 0.0076 | 0.0251 |  |  | 0.000592 |
| 7 | 0.0058 | 0.0202 |  |  | 0.001141 |
| 8 | 0.0058 | 0.0202 |  |  | 0.001536 |
| 9 | 0.0078 | 0.0195 |  |  | 0.001287 |
| 10 | 0.0057 | 0.0221 |  |  | 0.001234 |
| Average | 0.0074 | 0.0207 |  |  | 0.000793 |

Table 6.4: Performance on Easom


Figure 6.12: Average, methods are ordered in the same way as the table

UCMINF had problems. Both tolx and tolg had to be set to at least $10^{-8}$ before any iterations were performed, but after doing that it converged just fine. This happened because the first step had had a norm of its gradient of $8.2617 \cdot 10^{-5}$. The exact same happed with libopti. Maple could not solve the problem at all, stopping immediately.
minlbfgs was also unable to solve the problem, stalling at virtually any starting guess to any of the 4 stopping criteria regardless of what they were set to. It succeed at the starting guess $(3,3)$, but this would have been an unfair comparison.

Among the optimizers that could solve it, of which there were only 3 , libopti was by far the fastest because it isn't based on scripting.

The code used to take these samples can be found in Appendix C.5.

### 6.5 Ackley

Ackley's problem was defined by D. H. Ackley in 1987 in his paper about evolutionary algorithms and genetics.[Ack87] Originally, it was a 2-dimensional problem, pictured below, but was generalized by T. Bäck in 1996 to an $n$-dimensional problem.[Bäc96] This problem is difficult to solve due to its single global minimum but also cosine-periodic structure giving it an infinity of local minima in all directions. It is very easy for an algorithm to get "trapped" in one of these local minima.

This report deals with the relatively large problem where $n=5000$.

$$
\begin{equation*}
f(x)=20+\mathrm{e}-20 \mathrm{e}^{-1 / 5 \sqrt{\frac{\sum_{i=1}^{n} x_{i}{ }^{2}}{n}}}-\mathrm{e}^{\frac{\sum_{i=1}^{n} \cos \left(2 \pi x_{i}\right)}{n}} \tag{6.5}
\end{equation*}
$$

Here is a plot of the relevant area of the function when $n=2$ :


Figure 6.13: Minimum at $x_{i}=0$

First, a comparison of the CPU times, where the starting guess is is a sequence of 5000 random numbers between -3 and 3 , and the algorithm converges towards the minimum at all zeros. All times are measured in seconds.

| Attempt | UCMINF | FMINUNC | Maple 16 | minlbfgs | libopti |
| ---: | :---: | :---: | :---: | :---: | :---: |
| 1 |  |  | 3691.6 |  | 37.891406 |
| 2 |  |  |  |  | 37.551338 |
| 3 |  |  |  |  | 37.103554 |
| 4 |  |  |  |  | 38.802811 |
| 5 |  |  |  |  | 39.229581 |
| 6 |  |  |  |  | 38.581886 |
| 7 |  |  |  |  | 38.993073 |
| 8 |  |  |  |  | 38.768691 |
| 9 |  |  |  |  | 37.615502 |
| 10 |  |  |  |  | 36.913864 |
| Average |  |  |  |  | 38.145171 |

Table 6.5: Performance on Easom

The only algorithm that seemed able to converge correctly was libopti. UCMINF stopped itself in various valleys, but libopti did not. This happens because of the line search in UCMINF for MATLAB, which stops the algorithm because a potential precision error is detected. libopti does not check for this and carries on.

Maple took a very long time to solve the problem and converged to the wrong point, namely $x_{i} \approx 0.9685$. Even if it did converge correctly with a better starting guess, it would still take a very long time. Minlbfgs performs the same check that UCMINF does and stops, and FMINUNC does likewise.

The code used to take these samples can be found in Appendix C.6.


Figure 6.14: Solution of Ackley

As can be seen from these graphs (generated for the problem with $n=1000$ as $n=5000$ segfaulted due to too large memory requirements!), the solver constantly kept converging to lower values of $x$. The tolerance for the norm of $\nabla f(x)$ had to be set to a low number as it was often quite low.

### 6.6 Zakharov

Zakharov's function is of unknown origin to me, but I chose to feature it because it has an interesting phenomenon of a very flat valley along every second direction and power growth in the other directions, meaning that converging into this valley is trivial, but finding the actual minimum is very difficult, especially for higher dimensional problems and, unlike Beale's function, it is generalized to $n$ dimensions. The function was found at the University of Kyoto's web-page, and proper referencing was not provided.[Hed12b]

$$
\begin{equation*}
f(x)=\sum_{i=1}^{n} x_{i}^{2}+\left(\sum_{i=1}^{n} 1 / 2 i x_{i}\right)^{2}+\left(\sum_{i=1}^{n} 1 / 2 i x_{i}\right)^{4} \tag{6.6}
\end{equation*}
$$

Here is a plot of the relevant area of the function when $n=2$ :


Figure 6.15: Minimum at $x_{i}=0$

First, a comparison of the CPU times, where the starting guess is is a sequence of 1000 ones, and the algorithm converges towards the minimum at all zeros. All times are measured in seconds.

| Attempt | UCMINF | FMINUNC | Maple 16 | minlbfgs | libopti |
| ---: | :---: | :---: | :---: | :---: | :---: |
| 1 | 0.1927 | 1.1757 | $11384 s^{*}$ |  |  |
| 2 | 0.1886 | 1.1584 |  |  |  |
| 3 | 0.1890 | 1.1485 |  |  |  |
| 4 | 0.1895 | 1.1479 |  |  |  |
| 5 | 0.1879 | 1.1708 |  |  |  |
| 6 | 0.1899 | 1.1527 |  |  |  |
| 7 | 0.1880 | 1.1523 |  |  |  |
| 8 | 0.1880 | 1.1600 |  |  |  |
| 9 | 0.1988 | 1.2187 |  |  |  |
| 10 | 0.2144 | 1.2022 |  |  |  |
| Average | 0.1927 | 1.1687 |  |  |  |

Table 6.6: Performance on Zakharov

Only the MATLAB algorithms were capable of finishing this, most likely due to a special implementation, which is proprietary, of the norm function not present anywhere else. In the case of the MATLAB algorithms, they both solved the problem. UCMINF was fastest by far, roughly a factor of 10 . Maple 16 was able to start, but took so long I gave up.

The reason why libopti failed was because of the norm function. On the first iteration, $\Delta$ is 1 , and so the step should get normalized. However, we had no initial approximation of H , so we take the steepest descent direction. It scaled so badly that the step became so large, that when their powers of two were summed up, the sum wrapped around itself, going up through the negatives again, and the total result was about $1.5 \cdot 10^{0}$. Thus the step was not normalized at all. This could have been avoided with an initial approximation of the inverse Hessian, but for a 1000-dimensional problem it is virtually impossible to find accurately on a computer due to other scaling issues.

This problem gets passed on to the line search, which sees the massive step and ends up giving up because $\alpha$ becomes too small and takes no step at all. This means that the step length became 0 , and the algorithm terminates. Setting $\Delta_{0}$ to a large number didn't help due to rounding errors.

The reason why minlbfgs failed is unknown - however the results it returned were all NaN , Inf, or -Inf.

The code used to take these samples can be found in Appendix C.7.

## Chapter 7

## Conclusion

It is quite clear that libopti is a fast library. On the performance tests for small problems it stood up to an optimization library which claims to be 7-8 times faster than the GNU Scientific Library[ALG12b]. In addition, for all test problems but Zakharov it was much faster than the scripting based solutions. It could not solve Zakharov due to scaling problems, which mysteriously disappear in MATLAB. "Mysteriously" because it is a built-in non-viewable function.

One of the things I learned from this project is that C is fast. The reason why this library is so fast is precisely because it was written in C. C is one of the most efficient languages available and is a leading industry standard along with $\mathrm{C}++$. The other reason is that it is based upon the MATLAB implementations from Hans Bruun Nielsen, which are supposedly also very fast compared to similar software available in MATLAB, according to John Bagterp Jørgensen.

But the implementation carries other benefits as well. It is portable and can be used on embedded devices, depending only on BLAS and standard UNIX functions to run correctly. I also learned that, in some cases, separating system specific calls with generic calls that can be replaced depending on OS is quite important and very useful.

However, the implementation has a big problem: It uses function pointers. One of the things I've learned from this project is that function pointers is a very Cspecific feature that does not have direct counterparts in most other languages. This made running the algorithm from other languages impossible in most cases, possible in some cases with a bit of hacking.

Therefore one of the primary goals with this project were lost. This project is not older versions of FORTRAN, but it is possible to create a library that uses a routine from either of these two languages and calls it, then returns the result back to the language. It is directly callable from languages which have C as a subset of their own feature set, like C, Objective-C and Objective-C++, which was a nice little free feature.

Overall, I feel the project is a success. Despite its shortcomings in terms of porting to other languages it is still possible to do so and the speed and portability alone are enough to justify its use. The simple structure lays a strong foundation for the project to grow to include other types of optimization algorithms.

However, it can still be improved. Future ideas could be vectorization for more performance on multi-core processors, as well as enhancements to the algorithm in general and, of course, more optimization algorithms to use.

## Appendix $A$

## C library

## A. 1 Library Header

```
/*
* libopti.h
* Created on: Aug 15, 2012
    * Author: christian
#ifndef LIBOPTI_H_
#define LIBOPTI_H_
#ifdef __cplusplus //Ensure compatibility with C++
extern "C" {
#endif /* cplusplus */
//Written by: Christian Wichmann Moesgaard, Sep. }201
//Finds the minimizer to an unconstrained optimization problem given by fun()
    by using
/the Quasi-Newton BFGS method. Extra parameters may be sent using the void
    structure.
//Input: fun - A function handle to a function with the structure:
// *x - The address of an array of doubles representing the
// *x - The address of an array of doub
// *f - The address of the storage of the function
    evaluation
// *g - The address of an array of doubles. Will be filled
// the derivative of f(x).
```



```
1/
// *x - Pointer to the variables given to the function
// n - Number of variables given to the function
// *f - The address of the storage of the function evaluation
*f - The address of the storage of the function evaluation
the derivative of f(x)
*h - The search direction, the steplength multiplier,
*opts- An array with a few options:
choice: 1 = soft linesearch, 0 = exact linesearch
cp1: Constant 1 timed onto derivative of f at initial point
(not used if choice = 0)
cp2: Constant 2 timed onto derivative of f at initial point
maxeval:Maximum number of evaluation before quitting.
amax: Maximum tolerable search direction multiplier
Default: 0, 1e-3, 1e-3, 10, 10
    *perf- Some simple performance information from linesearch.
        Contains: search direction multiplier, final slope, number of
    evaluations
// *p - A pointer to a void structure that can be anything.
//Returns: 0 - Successful return
// -1 - Dynamic memory allocation failed.
// 1 - h is not downhill or it is so large and maxeval
// so small, that a better point was not found.
int opti_linesearch(void (*fun)(double *x, double *f, double *g, void *p),
    double *x,
    int n,
    double *f,
    double *g,
    double *h,
    double *opts,
    double *perf,
    void *p);
//Written by: Christian Wichmann Moesgaard, Aug. 2012
//Finds the minimizer of a 1D parabola which is given by:
//A point a, and a point b.
//The function value at a and the function value at b.
//The derivative of the function value at a
//Input: xfd - An array consisting of xfd = {a, b, f(a), f(b), f'(a)}
// n - The dimension of the problem original problem within
// which the parabola is to be constructed.
//Output: The minimizer of the parabola.
double opti_interpolate(double *xfd,
    int n);
//Written by: Christian Wichmann Moesgaard, Sep. 2012
//Finds f and g directly if h == 0. Otherwise, approximates g with forward
//difference approximation using an O(n+1) algorithm. If h is negative, uses
//backward difference.
//Input: fun - A function handle to a function with the structure:
// *x - The address of an array of doubles representing the
// point to take the function at.
*f - The address of the storage of the function
evaluation
// with
    *g - The address of an array of doubles. Will be filled
                                    the derivative of f(x).
/// *p - A pointer to a void structure that can be anything.
// *x - Pointer to the variables given to the function 
    *f - The address of the storage of the function evaluation
    *g - The address of an array of doubles. Will be filled with
                                    the derivative of f(x).
```

```
// h - The stepsize of the forward approximation. Can be any
    number.
    If h is 0, g is expected to be handed directly.
// *p - A pointer to a void structure that can be anything.
//Returns: 0 - Successfully returned the function and its derivative.
// -1 - Dynamic memory allocation failed.
int opti_findiff(void (*fun)(double *x, double *f, double *g, void *p),
    double *x,
    int n,
    double *f,
    double *g,
    double h,
    void *p);
//Written by: Christian W. Moesgaard, Sep. 2012
//Prints performance information to a file in such a way that the file
//has the iterations listed among the columns.
//
//Number of evaluations of f done in the iteration.
//The value of f at the iteration
//The norm of the derivative of the function at the iteration
//The linesearch limit \Delta at the value of the iteration
//The scaling factor for the step as given by the linesearch
//The slope of the function at the point in the direction of the step
//
//Input:*perf - The performance array given by ucminf
// maxiters - The maximum allowed iterations.
// Must be the same number passed to opts.
// Set to negative number to defeault to 100.
// filename - A string containing the filename.
//Returns: 0 - Successfully saved the data to file.
// -2 - Failed to open/write file. Nothing is saved.
int opti_printperf_tofile(double* perf,
    int maxiters,
    char* filename);
//Written by: Christian W. Moesgaard, Sep. 2012
//Prints performance information to a specified folder at the location the
//the program is run. Makes 7 subfiles named:
//
//evals.txt - Number of evaluations of f done in the iteration.
//fun.txt - The value of f at the iteration
//ng.txt - The norm of the derivative of the function at the iteration
//\Delta.txt - The linesearch limit \Delta at the value of the iteration
//am.txt - The scaling factor for the step as given by the linesearch
//finalslope.txt - The slope of the function at the point in the direction of
        the step
//x.txt - The contents of x at each iteration
//
//Input:*perf - The performance array given by ucminf
// maxiters - The maximum allowed iterations.
// Must be the same number passed to opts.
// Set to negative number to defeault to 100.
// foldername - A string containing the foldername from the location your
    program is run.
//Returns: 0 - Successfully saved the data to file.
// -2 - Failed to open/write file. Nothing is saved.
// -3 - File existed with name of folder to be created. Nothing saved.
// -4 - Folder could not be created. Check permissions or drive
int opti_printperf_tofolder(double* perf,
    double* xiter,
    int maxiters,
    int n,
    char* foldername);
```

```
|}19
//INTERNAL FUNCTIONS. NOT INTENDED FOR USAGE
//==============================================
//Takes a pointer to preallocated }n*n\mathrm{ array }M\mathrm{ and puts sets values such that
//it contains I.
void opti_deye(double *M, int n);
//Calculates the R^n-norm of the n-dimensional array x.
//Type can be 0 for inf-norm, or p \geq1 for p-norm.
double opti_norm(double *x, int n, int type);
#ifdef __cplusplus
}
#endif /* cplusplus */
#endif /* LIBOPTI_H_ */
```


## A. 2 BLAS usage

```
/*
    * use_blas.h
    * Created on: Sep 23, }201
    * Author: christian
    #ifndef USE_BLAS_H_
#define USE_BLAS_H_
int opti_initblas();
int opti_exitblas();
void opti_multmv(int dim, double scalar, double *A, double *x, double *y);
void opti_multmm(int rowA, int colA, double scalar, double *A, double *B,
    double *C);
double opti_multvv(int dim, double *x, double *y);
#endif /* USE_BLAS_H_ */
```


## A. 3 Create I matrix

```
/*
    * opti_deye.c
    * Created on: Nov 2, }201
```

```
* Author: christian
#ifdef __cplusplus
extern "C" {
#endif
//Written by: Christian W. Moesgaard, Sep. 2012
//Takes a pointer to an n-by-n array M and fills it with
//contents such that M is the identity matrix.
//Returns M by reference.
//
//Input: M - The performance array given by ucminf
// n - The size of n
//Output: void
void opti_deye(double *M, int n)
{
    int i;
    for (i = 0; i < n*n; ++i)
        if (i%n == i/n)
            M[i] = 1;
        else
            M[i] = 0;
    return;
}
#ifdef __cplusplus
}
#endif
```


## A. 4 Forward difference

```
* opti_findiff.c
    * Created on: Nov 2, 2012
        Author: christian
    * /
#ifdef __cplusplus
extern "C" {
#endif
#include <stdlib.h>
//Written by: Christian Wichmann Moesgaard, Sep. 2012
//Finds f and g directly if h == 0. Otherwise, approximates g with forward
//difference approximation using an O(n+1) algorithm. If h is negative, uses
//backward difference.
//Input: fun - A function handle to a function with the structure:
// *x - The address of an array of doubles representing the
point to take the function at.
// *f - The address of the storage of the function
    evaluation
// *g - The address of an array of doubles. Will be filled
with
// the derivative of f(x).
```

```
//
// *x - Pointer to the variables given to the function
// n - Number of variables given to the function
// *f - The address of the storage of the function evaluation
// *g - The address of an array of doubles. Will be filled with
// the derivative of f(x)
// h - The stepsize of the forward approximation. Can be any real
    number.
// If h is 0, g is expected to be handed directly.
//Returns: 0 - Successfully returned the function and its derivative.
// -1 - Dynamic memory allocation failed.
int opti_findiff(void (*fun) (double *x, double *f, double *g, void *p), double
        *x, int n, double *f, double *g, double h, void *p)
{
    int i; //Iterator
    double fplush; //Returned value for f
    double *gfplush = malloc(n*sizeof(double)); //g (unused)
    if (gfplush == NULL) //Memory allocation failure
    {
        free(gfplush);
        return -1;
    }
    fun(x, f, g, p);
    if (h == 0) //If h is set to 0 we expect useful value from g.
    {
        free(gfplush);
        return 0;
    }
    for (i = 0; i < n; ++i) //For each direction
    {
            x[i] += h; //Changing x in a new direction
            fun(x, &fplush, gfplush, p); //fplush has useful value!
            g[i] = (fplush - *f)/h; //Calculating finite difference
            x[i] -= h; //Going back from that direction again.
    } //x should now be exactly what it was, and g has been approximated!
    fun(x, f, gfplush, p); //Get proper value of f.
    return 0;
}
#ifdef __cplusplus
#endif
```


## A. 5 Quadratic Interpolation

```
/*
    * opti_interpolate.c
```

```
* Created on: Nov 2, }201
* Author: christian
*/
#ifdef __cplusplus
extern "C" {
#endif
#include <math.h>
//Written by: Christian Wichmann Moesgaard, Aug. 2012
//Finds the minimizer of a 1D parabola which is given by:
//A point a, and a point b.
//The function value at a and the function value at b.
//The derivative of the function value at a
//Input: xfd - An array consisting of xfd = {a, b, f(a), f(b), f'(a)}
// n - The dimension of the problem original problem within
// which the parabola is to be constructed.
//Output: The minimizer of the parabola.
double opti_interpolate(double *xfd, int n)
{
    //Minimizer of parabola given by xfd.
    double a = xfd[0], b = xfd[1], d = b - a, df = xfd[4];
    double C = (xfd[3] - xfd[2]) - (d*df);
    if (C \geq 5*n*pow(2.220446049250313,-16)*b) //Minimizer exists
    {
        double A = a - 0.5*df*((d*d)/C); d = 0.1*d;
        double t = a + d > A ? a + d : A;
        return t < b - d ? t : b - d; //Ensure significant resuction
    }
    else
        {
        return (a+b)/2;
    }
}
#ifdef __cplusplus
}
#endif
```


## A. 6 Line-search

```
/*
    * opti_linesearch.c
    * Created on: Nov 2, }201
        Author: christian
    */
#ifdef __cplusplus
extern "C" {
#endif
#include "../headers/libopti.h"
#include <math.h>
#include <string.h>
#include <stddef.h>
#include <stdlib.h>
```

```
#include "../headers/use_blas.h"
//Written by: Christian Wichmann Moesgaard, Sep. 2012
//Calculates a steplength of a step on a function, and puts the new point
//(scaled) point in x.
//Input: fun - A function handle to a function with the structure:
// *x - The address of an array of doubles representing the
// point to take the function at.
// *f - The address of the storage of the function
    evaluation
// *g - The address of an array of doubles. Will be filled
    with
                                    the derivative of f(x).
// * *p - A pointer to a void structure that can be anything.
// n - Number of variables given to the function
// *f - The address of the storage of the function evaluation
// *g - The address of an array of doubles. Will be filled with
// the derivative of f(x).
// *h - The search direction, the steplength multiplier,
// *opts- An array with a few options:
// choice: 1 = soft linesearch, 0 = exact linesearch
// cpl: Constant 1 timed onto derivative of f at initial point
        (not used if choice = 0)
                                    cp2: Constant 2 timed onto derivative of f at initial point
                                    maxeval:Maximum number of evaluation before quitting.
                                    amax: Maximum tolerable search direction multiplier
// Default: 0, 1e-3, 1e-3, 10, 10
// *perf- Some simple performance information from linesearch.
// Contains: search direction multiplier, final slope, number of
    evaluations
// *p - A pointer to a void structure that can be anything.
//Returns: 0 - Successful return
// -1 - Dynamic memory allocation failed.
// 1 - h is not downhill or it is so large and maxeval
// so small, that a better point was not found.
int opti_linesearch(void (*fun)(double *x, double *f, double *g, void *p),
                    double *x,
                    int n
                    double *f
                    double *g,
                    double *h,
                    double *opts,
                    double *perf,
                    void *p)
{
    //Define all data structures
    int i;
            //Iterator for simple for-loops
    //Initialization
    double f0 = *f;
            //Starting point function value
        double df0 = opti_multvv(n, h, g);
            Starting point derivative function value in LS direction
        double slope0, slopethr;
            //Linesearch stopping criteria information
        int info = 0;
                                    //Number of
            iterations and final slope value
        double eps = pow(2.220446049250313,-16);
            //Epsilon value for type double
        double *xn, *gn;
            Allocation for new x and new g
```

```
//Opts variables
double choice = 0, cp1 = 1e-3, cp2 = 1e-3, maxeval = 10, amax = 10,
    findiffh = 0.01; //Default options for
    stopping criteria
//Get an initial interval for am
double a = 0, fa = f0, dfa = df0;
    //am starts at 0, here f(a) = f0, df(a) = df0
double b = amax < 1 ? amax : 1; //Picking min value
        either amax or 1, depending on which is smaller
int stop = 0;
                                    //Used to mark stopping criteria found
//Declaring variables outside first while scope.
double fb, *xplusbtimesh, dfb;
//Declare variables outside second (refinement) while scope.
double c, fc, *xplusctimesh;
//Declare variables
xn = malloc(n*sizeof(double));
gn = malloc(n*sizeof(double));
xplusbtimesh = malloc(n*sizeof(double));
xplusctimesh = malloc(n*sizeof(double));
if (xn == NULL | | gn == NULL | |
    xplusbtimesh == NULL || xplusctimesh == NULL)
{ //If yes, deallocate memory and exit
    free(xn);
    free(gn);
    free(xplusbtimesh);
    free(xplusctimesh);
    return -1; //Allocation failed, not enough space for allocation
}
memcpy(xn,x,n*sizeof(double));
memcpy(gn,g,n*sizeof(double));
if (opts != NULL)
{
    choice = opts[0];
    cp1 = opts[1];
    cp2 = opts[2];
    maxeval = opts[3];
    amax = opts[4];
    findiffh = opts[5];
}
perf[0] = 0;
perf[1] = 1;
perf[2] = 0;
//Simple checks for descent condition
if (df0 \geq -10*eps*opti_norm(h, n, 2)*opti_norm(g, n, 2))
{
        free(xn);
        free(gn);
        free(xplusbtimesh);
        free(xplusctimesh);
        perf[2] = 0;
        return 1;
```



```
if (choice == 1) //Soft linesearch
{
        slope0 = cp1*df0;
        slopethr = cp2*df0;
}
else //Exact linesearch
{
    slope0 = 0;
    slopethr = cp1*fabs(df0);
}
while (!stop)
{
    info++;
    for (i = 0; i < n; ++i) xplusbtimesh[i] = x[i] + b*h[i];
    int findinfo = opti_findiff(fun, xplusbtimesh, n, &fb, g, findiffh, p)
    perf[2]++;
    if (findinfo == -1)
    {
        free(xn);
        free(gn);
        free(xplusbtimesh);
        free(xplusctimesh);
        return -1; //Allocation failed.
    }
    dfb = opti_multvv(n, g, h);
    if (fb < f0 + slope0*b) //New lower bound
    {
        perf[0] = b;
        perf[1] = dfb/df0;
        if (choice)
        {
            a = b;
            fa = fb;
            dfa = dfb;
            }
            for (i = 0; i < n; ++i) xn[i] = x[i] + b*h[i];
            memcpy(gn,g,n*sizeof(double));
            if (dfb < ((slopethr \leq 0)*slopethr) && (info < maxeval) && (b <
                amax))
            {
                //Augment right hand end
                if (!choice)
                {
                    a = b;
                fa = fb;
                dfa = dfb;
                }
                if (2.5*b \geq amax) b = amax;
                else b = 2*b;
            }
            else stop = 1;
    }
```

```
    else stop = 1;
} //phase 1: expand interval
if (stop \geq 0) //Everything OK so far. Check stopping criteria
    stop = ((info \geq maxeval) || ((b \geq amax) && (dfb < slopethr)) //Cannot
        improve
            || (choice && ((a > 0) && (dfb \geq slopethr)))); //OK
//If the above determines we must stop...
if (stop)
{
    memcpy(x,xn,n*sizeof(double));
    memcpy(g,gn,n*sizeof(double));
    *f = fb;
    free(xn);
    free(gn);
    free(xplusbtimesh);
    free(xplusctimesh);
    return info;
}
//Refine interval. Use auxiliary array xfd
double xfd[9] = {a, b, b, fa, fb, fb, dfa, dfb, dfb};
while (!stop)
{
    info++;
    double xfd_temp[5] = {xfd[0], xfd[1], xfd[3], xfd[4], xfd[6]};
    c = opti_interpolate(xfd_temp, n);
    for (i = 0; i < n; ++i) xplusctimesh[i] = x[i] + c*h[i];
    int findinfo = opti_findiff(fun, xplusctimesh, n, &fc, g, findiffh, p)
        ;
    perf[2]++;
    if (findinfo == -1)
    {
        free(xn);
        free(gn);
        free(xplusbtimesh);
        free(xplusctimesh);
        return -1; //Allocation failed.
    }
    xfd[2] = c;
    xfd[5] = fc;
    xfd[8] = opti_multvv(n, g, h);
    if (choice) //soft linesearch
        if (fc < f0 + slope0*c) //New lower bound
        {
            perf[0] = c;
            perf[1] = xfd[8]/df0;
            for (i = 0; i < n; ++i) xn[i] += c*h[i];
            memcpy(gn,g,n*sizeof(double));
            for (i = 0; i < 3; ++i) xfd[3*i] = xfd[3*i+2];
```

```
        stop = (xfd[8] > slopethr);
        }
        else //New upper bound
        for (i = 0; i < 3; ++i) xfd[3*i+1] = xfd[3*i+2];
        else //Exact line search
        {
            if (fc < (*f))
            {
                perf[0] = c;
                perf[1] = xfd[8]/df0;
                for (i = 0; i < n; ++i) xn[i] += c*h[i];
                memcpy(gn,g,n*sizeof(double));
                *f = fc;
            }
            if (xfd[8] < 0) for (i = 0; i < 3; ++i) xfd[3*i] = xfd[3*i+2];
            else for (i = 0; i < 3; ++i) xfd[3*i+1] = xfd[3*i
                +2];
            stop = ((fabs(xfd[8]) \leq slopethr) || (fabs(xfd[0] - xfd[1]) <
                    (cp2*xfd[1])));
        }
            stop = (stop || info \geq maxeval);
    } //End refinement
    memcpy(x,xn,n*sizeof(double));
    memcpy(g,gn,n*sizeof(double));
    *f = fc;
    free(xn);
    free(gn);
    free(xplusbtimesh);
    free(xplusctimesh);
    return 0;
}
#ifdef
    __cplusplus
}
#endif
```

\}
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## A. 7 Norm calculation

```
/*
opti_norm.c
Created on: Nov 2, 2012
    Author: christian
```

```
#ifdef __cplusplus
extern "C" {
#endif
#include <math.h>
//Written by: Christian W. Moesgaard, Sep. 2012
//Finds the norm of an n-length array x of double values.
//The third argument is the type of the norm, 0 is infinity norm.
//
//Input: x - The input array
// n - The length of x.
// type -
//Returns: A double with the result, should be positive.
double opti_norm(double *x, int n, int type)
{
    int i;
    double result = 0;
    if (type == 0) //Infinity norm
    {
        for (i = 0; i < n; ++i)
            if (result < fabs(x[i]))
                result = fabs(x[i]);
    }
    else
    {
        for (i = 0; i < n; ++i)
            result += pow(fabs(x[i]), type);
        result = pow(result, 1.0/(double) n);
    }
    return result;
}
#ifdef __cplusplus
}
#endif
```


## A. 8 Print performance to file

```
/*
    * opti_printperf_tofile.c
* Created on: Nov 2, 2012
    Author: christian
#ifdef __cplusplus //Ensure compatibility with C++.
extern "C" {
#endif /* cplusplus */
#include <stdio.h>
#include <stddef.h>
#include <stdlib.h>
#include <unistd.h>
```

```
#include <sys/types.h>
#include <sys/stat.h>
#include <errno.h>
#include <stddef.h>
#include <string.h>
//Written by: Christian W. Moesgaard, Sep. }201
//Prints performance information to a file in such a way that the file
//has the iterations listed among the columns.
//
//Number of evaluations of f done in the iteration.
//The value of f at the iteration
//The norm of the derivative of the function at the iteration
//The linesearch limit \Delta at the value of the iteration
//The scaling factor for the step as given by the linesearch
//The slope of the function at the point in the direction of the step
//
//Input:*perf - The performance array given by ucminf
// maxiters - The maximum allowed iterations.
// Must be the same number passed to opts.
// Set to negative number to defeault to 100.
// filename - A string containing the filename.
//Returns: 0 - Successfully saved the data to file.
// -2 - Failed to open/write file. Nothing is saved.
int opti_printperf_tofile(double* perf,
    int maxiters,
    char* filename)
{
    int iters = (int) perf[0];
    if (maxiters < 0) maxiters = 100;
    FILE *perffile;
    perffile = fopen(filename,"w+");
    if (perffile == NULL)
        return -2;
    fprintf(perffile, "Contents of rows: Evaluations, function value, norm of
        g, Delta, steplength multiplier, slope towards step at new x\n");
    int perftype, iter;
    for (perftype = 0; perftype < 6; ++perftype)
    {
        for (iter = 0; iter < iters-2; ++iter)
        {
            if (perftype == 0 && iter == 0)
                    fprintf(perffile, "%f, ", 1.0);
            else
                    fprintf(perffile,"%f, ",perf[maxiters*perftype + iter]);
        }
        fprintf(perffile,"%f.\n",perf[maxiters*perftype + iter]);
    }
    fclose(perffile);
    return 0;
}
#ifdef __cplusplus
}
#endif /* cplusplus */
```


## A. 9 Print performance to folder

```
* opti_printperf_tofolder.c
* Created on: Nov 2, }201
* Author: christian
*/
#ifdef __cplusplus //Ensure compatibility with C++.
extern "C" {
#endif /* cplusplus */
#include <stdio.h>
#include <stddef.h>
#include <stdlib.h>
#include <unistd.h>
#include <sys/types.h>
#include <sys/stat.h>
#include <errno.h>
#include <stddef.h>
#include <string.h>
//Written by: Christian W. Moesgaard, Sep. 2012
//Prints performance information to a specified folder at the location the
//program is run. Makes 7 subfiles named:
//
//evals.txt - Number of evaluations of f done in the iteration.
//fun.txt - The value of f at the iteration
//ng.txt - The norm of the derivative of the function at the iteration
//\Delta.txt - The linesearch limit \Delta at the value of the iteration
//am.txt - The scaling factor for the step as given by the linesearch
//finalslope.txt - The slope of the function at the point in the direction of
    the step
//x.txt - The contents of x at each iteration
//
//Input:*perf - The performance array given by ucminf
// maxiters - The maximum allowed iterations.
// Must be the same number passed to opts.
// Set to negative number to defeault to 100.
// foldername - A string containing the foldername from the location your
    program is run.
//Returns: 0 - Successfully saved the data to file.
// -2 - Failed to open/write file. Nothing is saved.
// -3 - File existed with name of folder to be created. Nothing saved.
// -4 - Folder could not be created. Check permissions or drive
int opti_printperf_tofolder(double* perf,
    double* xiter,
    int maxiters,
    int n,
    char* foldername)
{
    struct stat sb;
    int e;
    extern int errno;
    //Get info on the folder/file
    e = stat(foldername, &sb);
    //If something with this name already exists...
    if (e == 0)
    {
```

```
    if (sb.st_mode & 0100000) //If it's a file
                return -3; //File exists with foldername. Abort.
}
else
{
    if (errno == ENOENT)
    {
        e = mkdir(foldername, S_IRWXU);
        if (e != 0)
            return -4; //Folder could not be created. Check permissions or
                drive
    }
}
//Before we can use strcpy and strcat, we need the length of the string
size_t pathlen = strlen(foldername);
//Setting up iterations sequence
int iters = (int) perf[0];
if (maxiters < 0) maxiters = 100;
//Contents of rows:
//Evaluations,
//function value,
//norm of g,
//Delta,
//steplength multiplier,
//slope towards step at new x
//x as horizontal array
int perftype, iter;
char path[7][pathlen + 20];
for (perftype = 0; perftype < 7; ++perftype)
    strcpy(path[perftype],foldername);
//Names of files in new folder
strcat(path[0],"/evals.txt");
strcat(path[1],"/fun.txt");
strcat(path[2],"/ng.txt");
strcat(path[3],"/\Delta.txt");
strcat(path[4],"/am.txt");
strcat(path[5],"/finalslope.txt");
strcat(path[6],"/x.txt");
for (perftype = 0; perftype < 6; ++perftype)
{
    FILE *perffile;
    perffile = fopen(path[perftype], "w+");
    if (perffile == NULL)
        return -2; //Failed to open subfile
    for (iter = 0; iter < iters-2; ++iter)
    {
        if (perftype == 0 && iter == 0)
            fprintf(perffile, "%f ", 1.0);
        else
            fprintf(perffile,"%f ",perf[maxiters*perftype + iter]);
    }
    fprintf(perffile,"%f",perf[maxiters*perftype + iter]);
    fclose(perffile);
}
```

```
1 2 3
124 if (xiter != NULL)
125
126
127
128
129
131
132
134
135
136
137
138
139
141
143
144
146
}
#ifdef __cplusplus
}
#endif /* cplusplus */
```


## A. 10 Unconstrained BFGS minimization

```
// opti_ucminf.c
// Optiboxmac
//
// Created by Christian on 09/10/12.
//
#ifdef __cplusplus
extern "C" {
#endif
#include "../headers/libopti.h"
#include <math.h>
#include <float.h>
#include <stdio.h>
#include <string.h>
#include <stddef.h>
#include <stdlib.h>
#include "../headers/use_blas.h"
// Get machine-dependent NAN and INFINITY values.
# include <bits/nan.h>
# include <bits/inf.h>
```

```
//Written by: Christian Wichmann Moesgaard, Sep. 2012
//Finds the minimizer to an unconstrained optimization problem given by fun()
    by using
//the Quasi-Newton BFGS method. Extra parameters may be sent using the void
    structure.
//Input: fun - A function handle to a function with the structure:
// *x - The address of an array of doubles representing the
// point to take the function at.
// *f - The address of the storage of the function
    evaluation
// *g - The address of an array of doubles. Will be filled
    with
/// the derivative of f(x).
// *x - The starting guess x for the function. On exit, the optimal
    value for x.
                                - Number of variables given to the function
            *opts - An array containing:
                        \Delta - Initial value for largest stepsize used by the
        linesearching.
            tolg - The value which the norm of g is under when the 1st
        order KKT conditions are met.
    (x, n, 2)), stop.
    stopping.
        (). If set to 0, g is expected.
                                Warning: Using findiffh = 0 and not supplying g in
        fun WILL result in errors.
                            Default: 1, 1e-4, 1e-8, 100, 0
            *D - An array containing an initial estimation of the
                    inverse Hessian to the function. Set to NULL to start with
                    with I. On exit, a pointer to the Hessian.
                            Warning: Points to unclaimed memory if *D was set to NULL!
        *evalused - A pointer to an integer which will be filled with the number
        of evaluations.
                            Warning: NOT ITERATIONS.
// *perfinfo - A pointer that must point to an array of doubles of size 6*
    maxeval.
// Will contain performance information which can be printed
    using opti_printperf.
        *xiter - If null, nothing happens. Otherwise, contains a sequence of x
        for each iteration on exit.
// Must be preallocated to size n*maxiter (default n*100)
// *p - A void-pointer which can contain anything. Is passed through
    the function and
// all the way over to fun().
//Returns: -2 - BLAS failed to initialize. Error.
// -1 - memory allocation, error
// 0 - perfect starting guess, success
// 1 - Stepsize H became NaN, inf or -inf, error
// 2 - Stopped due to small derivative g, success
// 3 - Stopped due to small change in }x\mathrm{ , success
// 4 - Norm of stepsize became 0, success.
// 5 - Too many function evaluations, potential failure
int opti_ucminf(void (*fun)(double *x, double *f, double *g, void *p),
                    double *x,
                    int n,
                    double *opts,
                    double *D,
                int *evalused,
                double *perfinfo,
                double *xiter,
```

```
76
//Define all data structures
int i, j;
        //Iterator for simple for-loops
    int neval = 0, iter = 0;
    evaluations and iterations done
    double eps = pow(2.220446049250313,-16);
    smallest difference in doubles
    double Delta = 1, tolg = 1e-4, tolx = 1e-8; int maxeval = 100;
                                    //Options
    double f;
    //Function values
    double *g = malloc(n*sizeof(double)), *h = malloc(n*sizeof(double));
                                    //Values of derivative and steplength
    double *xp = malloc(n*sizeof(double)), *gp = malloc(n*sizeof(double));
                                    //Data for the internal parts of the loop
    double nx;
    //Norm of x
    double *tempD = NULL;
    Potentially necessary inverse hessian workspace
    int fst = 0;
    //Checking first iteration, 1 = yes, BOOL
    double ng;
    //Infinity norm of g
    double nh = 0;
    //Infinity norm of h
    int stop = 0, red = 0, more = 1;
        measurement
    double ngs[3];
    //Norm of gs_k, gs_k-1, gs_k-2
    double lsopts[6] = {1, 0.05, 0.99, 5, 2, 0.01};
                                    //Linesearch options
    double perf[3] = {0, 0, 0};
                                    //Linesearch
    performance
    int linfo = 0;
    //Info about number of iterations in the linesearch
    double *y = malloc(n*sizeof(double));
    double yh;
    //norm of y
    double *v = malloc(n*sizeof(double)), *w = malloc(n*sizeof(double));
                //Part of the BFGS update
    double a, yv;
    //ddot(y,v)
```

```
double thrx;
    //Used for 1st order KKT measurements
double findiffh = 0;
    finite difference approximation
//Initialize BLAS
int blasinfo = opti_initblas();
if (blasinfo) //Check if BLAS init failed
{
    free(g);
    free(h);
    free(xp);
    free(gp);
    free(y);
    free(v);
    free(w);
    return -2; //BLAS init fail
}
//Test allocation
if (g == NULL | | h == NULL | | xp == NULL | |
    gp == NULL | | y == NULL | | v == NULL || w == NULL)
{ //If yes, deallocate memory and exit
    free(g);
    free(h);
    free(xp);
    free(gp);
    free(y);
    free(v);
    free(w);
    return -1; //Allocation failed, not enough space for allocation
}
//Check options parameters and set them if necessary
if (opts != NULL)
{
    Delta = opts[0];
    tolg = opts[1];
    tolx = opts[2];
    maxeval = opts[3];
    findiffh = opts[4];
    lsopts[5] = findiffh;
}
linfo = opti_findiff(fun, x, n, &f, g, findiffh, p);
neval++;
if (xiter != NULL)
{
    for (i = 0; i < n; ++i)
            xiter[i + n*iter] = x[i];
}
if (linfo == -1)
{
    free(g);
    free(h);
```

```
    free(xp);
    free(gp);
    free(y);
    free (v);
    free (w);
    return -1; //Allocation failed.
}
//Finish initialization of g
ng = opti__norm(g, n, 0);
//Setup approximate inverse Hessian if missing.
if (D == NULL)
{
    tempD = malloc(n*n*sizeof(double));
    if (tempD == NULL)
    {
            free(g);
            free(h);
            free (xp)
            free(gp);
            free(y);
            free(v);
            free(w);
            return -1; //Allocation failed
        }
        opti_deye(tempD,n);
        D = tempD;
        fst = 1;
}
//Update performance log
if (perfinfo != NULL)
{
    perfinfo[iter ] = 0;
        perfinfo[iter + maxeval*1] = f;
        perfinfo[iter + maxeval*2] = ng;
        perfinfo[iter + maxeval*3] = Delta;
        perfinfo[iter + maxeval*4] = 0;
        perfinfo[iter + maxeval*5] = 0;
}
if (ng s tolg) //Check optimality condition
{
    free(g);
    free(h);
    free(xp);
    free(gp);
    free(y);
    free(v);
    free(w);
    free (tempD);
    return 0; //started optimal
}
else
{
    memset(h,0,n*sizeof(double));
    for (i = 0; i < 3; ++i) ngs[i] = ng;
}
//Start main loop
```

```
while (!(stop) && more)
    iter++;
    //Set previous values
    memcpy(xp,x,n*sizeof(double));
    memcpy(gp,g,n*sizeof(double));
    nx = opti_norm(x, n, 2);
    //Keep ngs up-to-date
    ngs[0] = ngs[1]; ngs[1] = ngs[2]; ngs[2] = ng;
    //Get step.
    opti_multmv(n, -1.0, D, g, h);
    //Check h for NAN's or other oddities.
    for (i = 0; i < n; ++i)
    {
        if (h[i] != h[i] || h[i] == INFINITY || h[i] == -INFINITY) //Check
            if inf, or if NaN.
        {
            free(g);
            free(h);
            free (xp);
            free(gp);
            free(y);
            free(v);
            free(w);
            free(tempD);
            return 1;
        }
    }
    nh = opti_norm(h, n, 2);
    red = 0;
    //Check optimality
    if (nh \leq tolx*(tolx + nx)) stop = 2;
    else
    {
        if (fst || nh > Delta)
        {
            for (i = 0; i < n; ++i) h[i] *= Delta/nh;
            nh = Delta;
            fst = 0; red = 1;
        }
        //Linesearch
        linfo = opti_linesearch(fun, x, n, &f, g, h, lsopts, perf, p);
        if (xiter != NULL)
            {
                for (i = 0; i < n; ++i)
                    xiter[i + n*iter] = x[i];
        }
        neval += perf[2]; //Counting evals
        if (perf[0] < 1) //Reduce Delta
        Delta *= 0.35;
        else if (red && (fabs(perf[1]) > 0.7)) //Expand \Delta
            Delta *= 3;
        //Update ||g|
        ng = opti_norm(g, n, 0);
        //Update h
        for (i = 0; i < n; ++i) h[i] = x[i] - xp[i];
        nh = opti_norm(h, n, 2);
```

```
        if (nh == 0)
        stop = 3;
        else
        {
        for (i = 0; i < n; ++i) y[i] = g[i] - gp[i];
        yh = opti_multvv(n, y, h);
        if (yh > sqrt(eps) * nh * opti_norm(y, n, 2))
        {
            //Update D using BFGS
                opti_multmv(n, 1.0, D, y, v);
                yv = opti_multvv(n, y, v);
                a = (1 + yv/yh)/yh;
                for (i = 0; i < n; ++i) w[i] = (a/2) *h[i] - v[i]/yh;
                //Calculating wh and hw and adding it to D, BFGS update
                for (i = 0; i < n; ++i)
                    for (j = 0; j < n; ++j)
                    {
                        D[i*n + j] += w[i]*h[j] + h[i]*w[j];
                    }
        }
        //Update performance benchmark
        if (perfinfo != NULL)
        {
            perfinfo[iter ] = perf[2];
        perfinfo[iter + maxeval*1] = f;
        perfinfo[iter + maxeval*2] = ng;
        perfinfo[iter + maxeval*3] = Delta;
        perfinfo[iter + maxeval*4] = perf[0];
        perfinfo[iter + maxeval*5] = perf[1];
    }
    //Check stopping criteria
        thrx = tolx*(tolx + opti_norm(x, n, 2));
        if (ng \leq tolg) stop = 1;
        else if (nh \leq thrx) stop = 2;
        else if (neval \geq maxeval) stop = 4;
        else Delta = Delta > 2*thrx ? Delta : 2*thrx;
        }
    }
}
//De-allocate variables
free(g);
free(h);
free(xp);
free(gp);
free(y);
free(v);
free(w);
iter++; //Fix off-of-one error
//State number of iterations
if (evalused != NULL)
    *evalused = neval;
//Insert number of iterations into perfinfo.
if (perfinfo != NULL)
    perfinfo[0] = iter;
//Initialize BLAS
blasinfo = opti_exitblas();
```

```
360 if (blasinfo) //Check if BLAS exit failed
361
\omega
364
365
366
367
368
370
372
373
374
375
76 }
378
\ w
~
381
382
383
384
#ifdef __cplusplus
87 }
388 #endif
```

Appendix B

## Wrappers to external libraries

## B. 1 Use Apple Accelerate

```
* use_accelerate.c
* Created on: Nov 2, 2012
        Author: christian
#ifdef __MACH
#include <Accelerate/Accelerate.h>
int opti_initblas()
{
    return 0;
}
int opti_exitblas()
{
    return 0;
}
void opti_multmv(int dim, double scalar, double *A, double *x, double *y)
{
        cblas_dgemv(CblasColMajor, CblasNoTrans, dim, dim, scalar, A, dim, x, 1,
            0.0, y, 1);
    return;
}
```

```
void opti_multmm(int rowA, int colA, double scalar, double *A, double *B,
        double *C)
{
    cblas_dgemm(CblasColMajor, CblasNoTrans, CblasNoTrans, rowA, rowA, colA,
        scalar, A, rowA, B, colA, 0.0, C, rowA);
    return;
}
double opti_multvv(int dim, double *x, double *y)
{
    return cblas_ddot(dim, x, 1, y, 1);
}
#endif /*__MACH___*/
```


## B. 2 Use ATLAS

```
/*
    * use_atlas.c
    * Created on: Nov 2, }201
    * Author: christian
    */
#ifndef __MACH__
#ifndef USE_CUDA_OPTI
#include <cblas.h>
int opti_initblas()
{
    return 0;
}
int opti_exitblas()
{
    return 0;
}
void opti_multmv(int dim, double scalar, double *A, double *x, double *y)
{
    cblas_dgemv(CblasColMajor, CblasNoTrans, dim, dim, scalar, A, dim, x, 1,
            0.0, y, 1);
    return;
}
void opti_multmm(int rowA, int colA, double scalar, double *A, double *B,
    double *C)
{
    cblas_dgemm(CblasColMajor, CblasNoTrans, CblasNoTrans, rowA, rowA, ColA,
        scalar, A, rowA, B, colA, 0.0, C, rowA);
    return;
}
double opti_multvv(int dim, double *x, double *y)
{
    return cblas_ddot(dim, x, 1, y, 1);
}
#endif /*USE_CUDA_OPTI*/
```

|39 \#endif /*__MACH__*/

## Appendix $C$

## Test runs

## C. 1 Apple Test

```
/// FirstViewController.m
// Optiboxios
//
// Created by Christian on 23/10/12.
// Copyright (c) 2012 Christian. All rights reserved.
//
#import "FirstViewController.h"
#import "liboptibox.h"
#import <math.h>
//Ackley function that must be called.
void ackley(double* x, double* f, double* df, void *p)
{
    double a, b, c; //Constants
    int i, n; //Iterator and dimensions
    a = *((double*) p);
    b}=*((double*) p+1)
    c = *((double*) p+2);
    n = *((double*) p+3);
    //Calculating function value
    double sum1 = 0, sum2 = 0; //Defining sums
```

```
    for (i = 0; i < (int) n; ++i)
    {
        sum1 += x[i]*x[i];
        sum2 += cos(c*x[i]);
    }
    *f = -a*exp(-b*sqrt((1.0/n)*sum1)) - exp((1.0/n)*sum2) + a + exp(1.0);
    //Calculating derivatives
    int j;
    for (j = 0; j < (int) n; ++j)
    { df[j] = 0; //Initializing to 0.
        df[j] += a*b*x[j]*exp(-(1.0/n)*b*sqrt (n*sum1))/sqrt(n*sum1);
        df[j] += -1.0/n*sin(c*x[j])*\operatorname{exp}(1.0/n*sum2);
    }
    return;
}
//======================
//Needs to be put into alltests!
#include <time.h>
#include <sys/time.h>
#ifdef __MACH__//If on a Mac, use Mach libraries
#include <mach/clock.h>
#include <mach/mach.h>
#endif // __MACH___
double opti_get_time()
{
    struct timespec ts;
#ifdef __MACH__ // OS X does not have clock_gettime, use clock_get_time
    clock_serv_t cclock;
    mach_timespec_t mts;
    host_get_clock_service(mach_host_self(), CALENDAR_CLOCK, &Cclock);
    clock_get_time(cclock, &mts);
    mach_port_deallocate(mach_task_self(), cclock);
    ts.tv_sec = mts.tv_sec;
    ts.tv_nsec = mts.tv_nsec;
#else
    clock_gettime(CLOCK_REALTIME, &ts);
#endif
    return (double) ts.tv_sec + (double) ts.tv_nsec * 1e-9;
}
//======================
@interface FirstViewController ()
@end
@implementation FirstViewController
@synthesize UIMainText;
- (void)viewDidLoad
{
    [super viewDidLoad];
    // Do any additional setup after loading the view, typically from a nib.
    //Generate random starting guess
```

```
    unsigned int iseed = (unsigned int)time(NULL);
    srand (iseed);
    //Number of inputs to n, number of max iterations
    int n = 20;
    int maxiters = 1000;
    double x[n];
    int i;
    //Randomly generate numbers
    for (i = 0; i < n; ++i)
    {
        x[i] = (rand()%600-300)/100.0;
    }
    //Define array with params
    double pi = 3.141592654;
    double p[] = {20, 0.2, 2*pi, (double) n};
    double perfinfo[maxiters*6];
    //Setting options
    double opts[] = {1.0, 0.0001, 0.00000001, maxiters, 0};
    //The function shall be called on the function, using x as starting guess,
    //with n values, opts shall be used for options, no initial approximation
    of inverse Hessian,
//want number of iterations used (not printed), want the performance info,
//we want all x iterations, and parameters p shall be passed.
double xinfo[n*maxiters];
double t1 = opti_get_time();
int ucminfr = opti_ucminf(ackley, x, n, opts, NULL, NULL, perfinfo, xinfo,
    (void*) p);
    double t2 = opti_get_time();
    //Results printed to folder
    //int folderinfo = opti_printperf_tofolder(perfinfo, xinfo, maxiters, n, " 
        testsackley");
    int folderinfo = 1;
    NSString * printthisfoo = [NSString stringWithFormat:
                                    @"Solve time: %f\nSave to folder info: %i\
                                    nSolution return: %i\n",
                                    t2 - t1, folderinfo, ucminfr];
    for (i = 0; i < n; ++i)
    {
        printthisfoo = [printthisfoo stringByAppendingString:[NSString
        stringWithFormat:@"%5.3f, ", x[i]]];
    }
UIMainText.text = printthisfoo;
}
- (void)didReceiveMemoryWarning
    [super didReceiveMemoryWarning];
    // Dispose of any resources that can be recreated.
}
@end
```

\{

## C. 2 Himmelblau

## C.2.1 MATLAB test

```
for i = 1:10
    tic,
    y(i,:) = ucminf(@himmelblau2,[1, 1]');
    t1(i) = toc;
end
time1 = sum(t1)/10;
for i = 1:10
    tic,
    x(i,:) = fminunc(@himmelblau,[1, 1]');
    t2(i) = toc;
end
time2 = sum(t2)/10;
t1, time1, t2, time2
```


## C.2.2 minlbfgs test

```
#include <stdlib.h>
#include <stdio.h>
#include <time.h>
#include <cmath>
#include "ap.h"
#include "minlbfgs.h"
using namespace std;
//Needs to be put into alltests!
#include <time.h>
#include <sys/time.h>
#ifdef __MACH__ //If on a Mac, use Mach libraries
#include <mach/clock.h>
#include <mach/mach.h>
#endif //__MACH__
double get_time()
{
    struct timespec ts;
#ifdef __MACH__ // OS X does not have clock_gettime, use clock_get_time
    clock_serv_t cclock;
    mach_timespec_t mts;
    host_get_clock_service(mach_host_self(), CALENDAR_CLOCK, &cclock);
    clock_get_time(cclock, &mts);
    mach_port_deallocate(mach_task_self(), cclock);
    ts.tv_sec = mts.tv_sec;
    ts.tv_nsec = mts.tv_nsec;
#else
#ifdef CLOCK_MONOTONIC
    clock_gettime(CLOCK_MONOTONIC, &ts);
#else
```

```
    clock_gettime(CLOCK_REALTIME, &ts);
#endif
#endif
    return (double) ts.tv_sec + (double) ts.tv_nsec * 1e-9;
}
void himmelblau(double* x, double* f, double* df, void *p)
{
    *f = pow(x[0]*x[0] + x[1] - 11,2) + pow(x[0] + x[1]*x[1] - 7,2);
    df[0] = 2*(2*x[0]*(x[0]*x[0] + x[1] - 11) + x[0] + x[1]*x[1] - 7);
    df[1] = 2*(-11+x[0]*x[0] + x[1] + 2*x[1]*(-7 + x[0] + x[1]*x[1]));
    return;
}
/ / ========================
int main(int argc, char **argv)
{
    int n = 2;
    int m = 1;
    minlbfgsstate state;
    minlbfgsreport rep;
    ap::real_1d_array s;
    double x[n];
    double time = 0;
    n = 2;
    m = 1;
    s.setlength(n);
    //f and g
    double f;
    double g[n];
    for (int i = 0; i < 10; ++i)
    {
    s(0) = 1;
    s(1) = 1;
    double t1 = get_time();
    minlbfgscreate(n, m, s, state);
    minlbfgssetcond(state, 0.0, 0.0, 0.0001, 0);
    while(minlbfgsiteration(state))
    {
        if( state.needfg )
        {
            for (int k = 0; k < n; ++k)
            x[k] = state.x(k);
            himmelblau(x, &f, g, NULL);
            state.f = f;
            for (int k = 0; k < n; ++k)
                        state.g(k) = g[k];
            }
    }
    minlbfgsresults(state, s, rep);
    double t2 = get_time();
    time += t2 - t1;
```

```
printf("Solve time: %f\n", t2 - t1);
}
printf("Result: (%f, %f)\n", state.x(0), state.x(1));
printf("Average solve time: %f\n", time /= 10);
return 0;
}
```


## C.2.3 libopti test

```
/*
    * himmbelblau.h
* Created on: Nov 3, }201
* Author: christian
*/
#ifndef HIMMELBLAU_H_
#define HIMMELBLAU_H_
#include <math.h>
#include <stddef.h>
void himmelblau(double* x, double* f, double* df, void *p)
{
        *f = pow(x[0]*x[0] + x[1] - 11,2) + pow(x[0] + x[1]*x[1] - 7,2);
    df[0] = 2*(2*x[0]*(x[0]*x[0] + x[1] - 11) + x[0] + x[1]*x[1] - 7);
    df[1] = 2*(-11+x[0]*x[0] + x[1] + 2*x[1]*(-7 + x[0] + x[1]*x[1]));
    return;
}
//Example of using the algorithm.
double TestHimmelblau()
{
    //Number of inputs, number of max iterations
    int n = 2, maxiters = 100;
    //Setting options.
    // \Delta - Initial value for largest stepsize used by the
        linesearching.
        tolg - The value which the norm of g is under when the
        1st order KKT conditions are met.
    // tolx - If the stepsize is less than tolx*(tolx +
        opti_norm(x, n, 2)), stop.
        // maxeval - The maximum number of tolerable iterations
        before stopping.
        // findiffh - Used in the finite difference approximation for
        fun(). If set to 0, df is expected.
                            Warning: Using findiffh = 0 and not supplying g
        in fun WILL result in errors.
        // Default: 1, 1e-4, 1e-8, 100, 0
        double opts[] = {1.0, 1e-4, 1e-8, maxiters, 0};
        //The function shall be called on the function, using x as starting guess,
```

```
    //with n values, opts shall be used for options, no initial approximation
    of inverse Hessian,
    //want number of iterations used (not printed), want the performance info,
    //we want all x iterations, no parameters.
    //Starting guess 1
    double x1[2] = {1, 1};
    double t1 = opti_get_time();
    int ucminfr = opti_ucminf(himmelblau, x1, n, opts, NULL, NULL, NULL, NULL,
        NULL);
    double t2 = opti_get_time();
    return t2 - t1;
}
#endif /* HIMMELBLAU_H_ */
```


## C. 3 Rosenbrock

## C.3.1 MATLAB test

```
for i = 1:10
    tic,
    y(i,:) = ucminf(@rosenbrock2,[4, 2]');
    t1(i) = toc;
end
time1 = sum(t1)/10;
for i = 1:10
    tic,
    x(i,:) = fminunc(@rosenbrock,[4, 2]');
    t2(i) = toc;
end
time2 = sum(t2)/10;
t1, time1, t2, time2
```


## C.3.2 minlbfgs test

```
#include <stdlib.h>
#include <stdio.h>
#include <time.h>
#include <cmath>
#include "ap.h"
#include "minlbfgs.h"
using namespace std;
```

```
//Needs to be put into alltests!
#include <time.h>
#include <sys/time.h>
#ifdef __MACH__ //If on a Mac, use Mach libraries
#include <mach/clock.h>
#include <mach/mach.h>
#endif //__MACH__
double get_time()
{
    struct timespec ts;
#ifdef __MACH__ // OS X does not have clock_gettime, use clock_get_time
    clock_serv_t cclock;
    mach_timespec_t mts;
    host_get_clock_service(mach_host_self(), CALENDAR_CLOCK, &cclock);
    clock_get_time(cclock, &mts);
    mach_port_deallocate(mach_task_self(), cclock);
    ts.tv_sec = mts.tv_sec;
    ts.tv_nsec = mts.tv_nsec;
#else
#ifdef CLOCK_MONOTONIC
    clock_gettime(CLOCK_MONOTONIC, &ts);
#else
    clock_gettime(CLOCK_REALTIME, &ts);
#endif
#endif
    return (double) ts.tv_sec + (double) ts.tv_nsec * 1e-9;
}
void rosenbrock(double* x, double* f, double* df, void *p)
{
        *f = pow((double) (1 - x[0]), (double) 2) + 100 * pow((double) (x[1] - pow
            ((double) x[0], (double) 2)), (double) 2);
        df[0] = -2 + 2 * x[0] - 400 * (x[1] - pow((double) x[0], (double) 2)) * x
            [0];
        df[1] = 200 * x[1] - 200 * pow((double) x[0], (double) 2);
        return;
}
// =======================
int main(int argc, char **argv)
{
    int n = 2;
    int m = 1;
    minlbfgsstate state;
    minlbfgsreport rep;
    ap::real_1d_array s;
    double x[n];
    double time = 0;
    n = 2;
    m = 1;
    s.setlength(n);
    //f and g
    double f;
    double g[n];
    for (int i = 0; i < 10; ++i)
    {
```

```
    s(0) = 4;
    s(1) = 2;
    double t1 = get_time();
    minlbfgscreate(n, m, s, state);
    minlbfgssetcond(state, 0.0, 0.0, 0.0001, 0);
    while(minlbfgsiteration(state))
    {
        if( state.needfg )
    {
        for (int k = 0; k < n; ++k)
            x[k] = state.x(k);
        rosenbrock(x, &f, g, NULL);
        state.f = f;
        for (int k = 0; k < n; ++k)
            state.g(k)=g[k];
        }
    }
    minlbfgsresults(state, s, rep);
    double t2 = get_time();
    time += t2 - t1;
    printf("Solve time: %f\n", t2 - t1);
    }
    printf("Result: (%f, %f)\n", state.x(0), state.x(1));
    printf("Average solve time: %f\n", time /= 10);
    return 0;
}
```


## C.3.3 libopti test

```
/*
    * rosenbrock.h
    * Created on: Aug 18, 2012
        Author: christian
    */
#ifndef ROSENBROCK_H_
#define ROSENBROCK_H_
#include <math.h>
#include <stddef.h>
void rosenbrock(double* x, double* f, double* df, void *p)
{
        *f = pow((double) (1 - x[0]), (double) 2) + 100 * pow((double) (x[1] - pow
            ((double) x[0], (double) 2)), (double) 2);
        df[0] = -2 + 2 * x[0] - 400 * (x[1] - pow((double) x[0], (double) 2)) * x
            [0];
        df[1] = 200 * x[1] - 200 * pow((double) x[0], (double) 2);
```

```
    return;
}
//Example of using the algorithm.
double TestRosenbrock()
{
    //Number of inputs to n, number of max iterations
    int maxiters = 100;
    int n = 2;
    double x[2] = {4, 2};
    //Setting options
    double opts[] = {1.0, 0.0001, 0.00000001, maxiters, 0};
    //The function shall be called on the function, using x as starting guess,
    //with n values, opts shall be used for options, no initial approximation
        of inverse Hessian,
    double t1 = opti_get_time();
    int ucminfr = opti_ucminf(beale, x, n, opts, NULL, NULL, NULL, NULL, NULL)
        ;
    double t2 = opti_get_time();
    return t2 - t1;
}
#endif /* ROSENBROCK_H_ */
```


## C. 4 Beale

## C.4.1 MATLAB test

```
for i = 1:10
    tic,
    y(i,:) = ucminf(@beale2,[4, 2]');
    t1(i) = toc;
end
time1 = sum(t1)/10;
for i = 1:10
    tic,
    x(i,:) = fminunc(@beale,[4, 2]');
    t2(i) = toc;
end
time2 = sum(t2)/10;
t1, time1, t2, time2
```


## C.4.2 minlbfgs test

```
#include <stdlib.h>
#include <stdio.h>
#include <time.h>
#include <cmath>
#include "ap.h"
#include "minlbfgs.h"
using namespace std;
//Needs to be put into alltests!
#include <time.h>
#include <sys/time.h>
#ifdef __MACH__ //If on a Mac, use Mach libraries
#include <mach/clock.h>
#include <mach/mach.h>
#endif //__MACH__
double get_time()
{
    struct timespec ts;
#ifdef __MACH__// OS X does not have clock_gettime, use clock_get_time
    clock_serv_t cclock;
    mach_timespec_t mts;
    host_get_clock_service(mach_host_self(), CALENDAR_CLOCK, &cclock);
    clock_get_time(cclock, &mts);
    mach_port_deallocate(mach_task_self(), cclock);
    ts.tv_sec = mts.tv_sec;
    ts.tv_nsec = mts.tv_nsec;
#else
#ifdef CLOCK_MONOTONIC
    clock_gettime(CLOCK_MONOTONIC, &ts);
#else
    clock_gettime(CLOCK_REALTIME, &ts);
#endif
#endif
    return (double) ts.tv_sec + (double) ts.tv_nsec * 1e-9;
}
void beale(double* x, double* f, double* df, void *p)
{
        *f = pow(0.15e1 - x[0] + x[0] * x[1], 0.2e1) + pow(0.225e1 - x[0] + x[0] *
            pow(x[1], 0.2e1), 0.2e1) + pow(0.2625e1 - x[0] + x[0] * pow(x[1],
            0.3e1), 0.2e1);
    df[0] = 0.2e1 * (0.15e1 - x[0] + x[0] * x[1]) * (-0.1e1 + x[1]) + 0.2e1 *
                (0.225e1 - x[0] + x[0] * pow (x[1], 0.2e1)) * (-0.1e1 + pow(x[1], 0.2
                e1)) + 0.2e1 * (0.2625e1 - x[0] + x[0] * pow(x[1], 0.3e1)) * (-0.1e1
                + pow(x[1], 0.3e1));
    df[1] = 0.2e1 * (0.15e1 - x[0] + x[0] * x[1]) * x[0] + 0.4e1 * (0.225e1 -
        x[0] + x[0] * pow(x[1], 0.2e1)) * x[0] * x[1] + 0.6e1 * (0.2625e1 - x
        [0] + x[0] * pow(x[1], 0.3e1)) * x[0] * pow(x[1], 0.2e1);
        return;
}
//========================
int main(int argc, char **argv)
{
    int n = 2;
    int m = 1;
    minlbfgsstate state;
    minlbfgsreport rep;
    ap::real_1d_array s;
```

```
double x[n];
double time = 0;
    n = 2;
    m = 1;
    s.setlength(n);
    //f and g
    double f;
    double g[n];
    for (int i = 0; i < 10; ++i)
    {
    s(0) = 4;
    s(1) = 2;
    double t1 = get_time();
    minlbfgscreate(n, m, s, state);
    minlbfgssetcond(state, 0.0, 0.0, 0.0001, 0);
    while(minlbfgsiteration(state))
    {
        if( state.needfg )
        {
        for (int k = 0; k < n; ++k)
            x[k] = state.x(k);
        beale(x, &f, g, NULL);
        state.f = f;
        for (int k = 0; k < n; ++k)
            state.g(k) = g[k];
        }
    }
    minlbfgsresults(state, s, rep);
    double t2 = get_time();
    time += t2 - t1;
    printf("Solve time: %f\n", t2 - t1);
    }
    printf("Result: (%f, %f)\n", state.x(0), state.x(1));
    printf("Average solve time: %f\n", time /= 10);
    return 0;
}
```


## C.4.3 libopti test

```
/*
* beale.h
* Created on: Aug 18, }201
    * Author: christian
```

```
#ifndef BEALE_H_
#define BEALE_H_
#include <math.h>
void beale(double* x, double* f, double* df, void *p)
{
    *f = pow(0.15e1 - x[0] + x[0] * x[1], 0.2e1) + pow(0.225e1 - x[0] + x[0] *
        pow(x[1], 0.2e1), 0.2e1) + pow(0.2625e1 - x[0] + x[0] * pow(x[1],
        0.3e1), 0.2e1);
    df[0] = 0.2e1 * (0.15e1 - x[0] + x[0] * x[1]) * (-0.1e1 + x[1]) + 0.2e1 *
        (0.225e1 - x[0] + x[0] * pow(x[1], 0.2e1)) * (-0.1e1 + pow(x[1], 0.2
        e1)) + 0.2e1 * (0.2625e1 - x[0] + x[0] * pow(x[1], 0.3e1)) * (-0.1e1
        + pow(x[1], 0.3e1));
    df[1] = 0.2e1 * (0.15e1 - x[0] + x[0] * x[1]) * x[0] + 0.4e1 * (0.225e1 -
        x[0] + x[0] * pow(x[1], 0.2e1)) * x[0] * x[1] + 0.6e1 * (0.2625e1 - x
        [0] + x[0] * pow(x[1], 0.3e1)) * x[0] * pow(x[1], 0.2e1);
    return;
}
//Example of using the algorithm.
double TestBeale()
{
    //Number of inputs, number of max iterations
    int n = 2, maxiters = 100;
    //Setting options.
    // \Delta - Initial value for largest stepsize used by the
        linesearching.
    // tolg - The value which the norm of g is under when the
        1st order KKT conditions are met.
    opti_norm(x, n, 2)), stop.
    // maxeval - The maximum number of tolerable iterations
        before stopping.
            findiffh - Used in the finite difference approximation for
        fun(). If set to 0, df is expected.
                            Warning: Using findiffh = 0 and not supplying g
        in fun WILL result in errors.
    // Default: 1, 1e-4, 1e-8, 100, 0
    double opts[] = {1.0, 1e-4, 1e-8, maxiters, 0};
    //The function shall be called on the function, using x as starting guess,
    //with n values, opts shall be used for options, no initial approximation
        of inverse Hessian,
    //Starting guess 1
    double x1[2] = {4, 2};
    double t1 = opti__get_time();
    int ucminfr = opti_ucminf(beale, x1, n, opts, NULL, NULL, NULL, NULL, NULL
        );
    double t2 = opti_get_time();
    return t2 - t1;
}
#endif /* BEALE_H_ */
```


## C. 5 Easom

## C.5.1 MATLAB test

```
for i = 1:10
    tic,
    [y, info, perf] = ucminf(@easom2,[1, 1]', [1 1e-4 1e-8 100]);
    t1(i) = toc;
end
time1 = sum(t1)/10;
for i = 1:10
    tic,
    x(i,:) = fminunc(@easom,[1, 1]');
    t2(i) = toc;
end
time2 = sum(t2)/10;
t1, time1, t2, time2
```


## C.5.2 minlbfgs test

```
#include <stdlib.h>
#include <stdio.h>
#include <time.h>
#include <cmath>
#include "ap.h"
#include "minlbfgs.h"
using namespace std;
//Needs to be put into alltests!
#include <time.h>
#include <sys/time.h>
#ifdef __MACH__ //If on a Mac, use Mach libraries
#include <mach/clock.h>
#include <mach/mach.h>
#endif //___MACH__
double get_time()
{
    struct timespec ts;
#ifdef __MACH__ // OS X does not have clock_gettime, use clock_get_time
    clock_serv_t cclock;
    mach_timespec_t mts;
    host_get_clock_service(mach_host_self(), CALENDAR_CLOCK, &cclock);
    clock_get_time(cclock, &mts);
    mach_port_deallocate(mach_task_self(), cclock);
    ts.tv_sec = mts.tv_sec;
    ts.tv_nsec = mts.tv_nsec;
#else
#ifdef CLOCK_MONOTONIC
    clock_gettime(CLOCK_MONOTONIC, &ts);
```

```
#else
    clock_gettime(CLOCK_REALTIME, &ts);
#endif
#endif
    return (double) ts.tv_sec + (double) ts.tv_nsec * 1e-9;
}
void easom(double* x, double* f, double* df, void *p)
{
    double pi = 3.14159265358979323846;
    *f = - cos(x[0])*\operatorname{cos(x[1])*exp(-pow((x[0]-pi),2) - pow((x[1] - pi),2));}
    df[0] = sin(x[0])*\operatorname{cos}(x[1])*exp(-pow((x[0]-pi),2) - pow((x[1] - pi),2))
        + -cos(x[0])*\operatorname{cos}(x[1])*(-2*x[0] + 2*pi)*exp(-pow((x[0]-pi),2) - pow
                ((x[1] - pi),2));
    df[1] = cos(x[0])*sin(x[1])*exp(-pow((x[0]-pi),2) - pow((x[1] - pi),2))
        + - cos(x[0])*\operatorname{cos}(x[1])*(-2*x[1] + 2*pi)*exp(-pow((x[0]-pi),2) - pow
                ((x[1] - pi),2));
}
/ / ========================
int main(int argc, char **argv)
{
    int n = 2;
    int m = 1;
    minlbfgsstate state;
    minlbfgsreport rep;
    ap::real_1d_array s;
    double x[n];
    double time = 0;
    n = 2;
    m = 1;
    s.setlength(n);
    //f and g
    double f;
    double g[n];
    for (int i = 0; i < 10; ++i)
    {
    s(0) = 1;
    s(1) = 1;
    double t1 = get_time();
    minlbfgscreate(n, m, s, state);
    minlbfgssetcond(state, 1e-10, 1e-10, 1e-10, 100);
    while(minlbfgsiteration(state))
    {
        if( state.needfg )
        {
            for (int k = 0; k < n; ++k)
                x[k] = state.x(k);
            easom(x, &f, g, NULL);
            state.f = f;
            for (int k = 0; k < n; ++k)
                state.g(k) = g[k];
        }
    }
    minlbfgsresults(state, s, rep);
```

```
95 double t2 = get_time();
time += t2 - t1;
    printf("Solve time: %f\n", t2 - t1);
    }
    printf("Result: (%f, %f)\n", state.x(0), state.x(1));
    printf("Result: (%f, %f)\n", state.g(0), state.g(1));
    printf("Result: %f\n", state.f);
    printf("Average solve time: %f\n", time /= 10);
    return 0;
}
```


## C.5.3 libopti test

```
/*
    * easom.h
* Created on: Aug 18, }201
    * Author: christian
*/
#ifndef EASOM_H_
#define EASOM_H_
#include <math.h>
#include <stddef.h>
#include <stdio.h>
void easom(double* x, double* f, double* df, void *p)
{
    double pi = 3.14159265358979323846;
    *f = - cos (x[0])*\operatorname{cos}(x[1])*exp(-pow((x[0]-pi),2) - pow((x[1] - pi),2));
    df[0] = sin(x[0])*\operatorname{cos}(x[1])*\operatorname{exp}(-\operatorname{pow}((x[0]-pi),2)-\operatorname{pow}((x[1] - pi),2))
        + -cos(x[0])*\operatorname{cos}(x[1])*(-2*x[0] + 2*pi)*exp(-pow((x[0]-pi),2) - pow
        ((x[1] - pi),2));
    df[1] = cos(x[0])*\operatorname{sin}(x[1])*\operatorname{exp}(-pow((x[0]-pi),2) - pow((x[1] - pi),2))
        + - cos (x[0])*\operatorname{cos}(x[1])*(-2*x[1] + 2*pi)*exp(-pow((x[0]-pi),2) - pow
            ((x[1] - pi),2));
}
//Example of using the algorithm.
double TestEasom()
{
    //Number of inputs, number of max iterations
    int n = 2, maxiters = 100;
    //Setting options.
    // \Delta - Initial value for largest stepsize used by the
        linesearching.
    // tolg - The value which the norm of g is under when the
        1st order KKT conditions are met.
                        tolx - If the stepsize is less than tolx*(tolx +
        opti_norm(x, n, 2)), stop.
    // maxeval - The maximum number of tolerable iterations
        before stopping.
```

```
    // findiffh - Used in the finite difference approximation for
        fun(). If set to 0, df is expected.
            Warning: Using findiffh = 0 and not supplying g
        in fun WILL result in errors.
    // Default: 1, 1e-4, 1e-8, 100, 0
    double opts[] = {1.0, 1e-8, 1e-8, maxiters, 0};
    //The function shall be called on the function, using x as starting guess,
    //with n values, opts shall be used for options, no initial approximation
        of inverse Hessian,
    //Starting guess 1
    double x1[2] = {1, 1};
    double t1 = opti_get_time();
    int ucminfr = opti_ucminf(easom, x1, n, opts, NULL, NULL, NULL, NULL, NULL
        );
        double t2 = opti_get_time();
    double df[2], f;
    easom(x1, &f, df, NULL);
    printf("(%f, %f)\n", x1[0],x1[1]);
    return t2 - t1;
}
#endif /* EASOm_H_ */
```


## C. 6 Ackley

## C.6.1 MATLAB test

```
for i = 1:10
    tic,
    yin = (rand([5000,1])-0.5)*6;
    [y, info, perf] = ucminf(@ackley2,yin, [1 1e-8 1e-8 1000]);
    [f g] = ackley2(y);
    f, h = norm(g),
    t1(i) = toc;
end
time1 = sum(t1)/10;
for i = 1:10
    tic,
    xin = (rand([5000,1])-0.5)*6;
    x = fminunc(@ackley,xin);
    t2(i) = toc;
end
time2 = sum(t2)/10;
t1, time1, t2, time2
```


## C.6.2 minlbfgs test

```
#include <stdlib.h>
#include <stdio.h>
#include <cmath>
#include "ap.h"
#include "minlbfgs.h"
using namespace std;
//Needs to be put into alltests!
#include <time.h>
#include <sys/time.h>
#ifdef __MACH__ //If on a Mac, use Mach libraries
#include <mach/clock.h>
#include <mach/mach.h>
#endif //___MACH__
double get_time()
{
    struct timespec ts;
#ifdef __MACH__ // OS X does not have clock_gettime, use clock_get_time
    clock_serv_t cclock;
    mach_timespec_t mts;
    host_get_clock_service(mach_host_self(), CALENDAR_CLOCK, &cclock);
    clock_get_time(cclock, &mts);
    mach_port_deallocate(mach_task_self(), cclock);
    ts.tv_sec = mts.tv_sec;
    ts.tv_nsec = mts.tv_nsec;
#else
#ifdef CLOCK_MONOTONIC
    clock_gettime(CLOCK_MONOTONIC, &ts);
#else
    clock_gettime(CLOCK_REALTIME, &ts);
#endif
#endif
        return (double) ts.tv_sec + (double) ts.tv_nsec * 1e-9;
}
void ackley(double* x, double* f, double* df, void *p)
{
    double a, b, c; //Constants
    int i, n; //Iterator and dimensions
    c = 2*M_PI;
    n = 5000;
    //Calculating function value
    double sum1 = 0, sum2 = 0; //Defining sums
    for (i = 0; i < (int) n; ++i)
        {
            sum1 += x[i]*x[i];
            sum2 += cos(c*x[i]);
        }
    *f = -a*exp(-b*sqrt((1.0/n)*sum1)) - exp((1.0/n)*sum2) + a + exp(1.0);
    //Calculating derivatives
    int j;
    for (j = 0; j < (int) n; ++j)
```

```
    {
    df[j] = 0; //Initializing to 0.
    df[j] += a*b*x[j]*exp(-(1.0/n)*b*sqrt(n*sum1))/sqrt(n*sum1);
    df[j] += -1.0/n*sin(c*x[j])*exp(1.0/n*sum2);
    }
    return;
}
// =======================
int main(int argc, char **argv)
{
    int n = 5000;
    int m = 1;
    minlbfgsstate state;
    minlbfgsreport rep;
    ap::real_1d_array s;
    double x[n];
    double timet = 0;
    s.setlength(n);
    //f and g
    double f;
    double g[n];
    for (int i = 0; i < 10; ++i)
    {
    //Generate random starting guess
    unsigned int iseed = (unsigned int) time(NULL);
    srand (iseed);
    //Randomly generate numbers
    for (int k = 0; k < n; ++k) s(k) = (rand()%600 - 300)/100.0;
    double t1 = get_time();
    minlbfgscreate(n, m, s, state);
    minlbfgssetcond(state, 1e-10, 1e-10, 1e-10, 1000);
    while(minlbfgsiteration(state))
    {
        if( state.needfg )
        {
            for (int k = 0; k < n; ++k)
                x[k] = state.x(k);
            ackley(x, &f, g, NULL);
            state.f = f;
                for (int k = 0; k < n; ++k)
                state.g(k) = g[k];
            }
    }
    minlbfgsresults(state, s, rep);
    double t2 = get_time();
    timet += t2 - t1;
```

```
127 printf("Solve time: %f\n", t2 - t1);
128 }
129
130
132
133
}
```


## C.6.3 libopti test

```
** Ackley.h
* Created on: Aug 17, 2012
    * Author: christian
    * /
#ifndef ACKLEY_H_
#define ACKLEY_H_
#include <math.h>
void ackley(double* x, double* f, double* df, void *p)
{
    double a, b, c; //Constants
    int i, n; //Iterator and dimensions
    a = *((double*) p);
    b}=*((\mathrm{ double*) p+1);
    c = *((double*) p+2);
    n = *((double*) p+3);
    //Calculating function value
    double sum1 = 0, sum2 = 0; //Defining sums
    for (i = 0; i < (int) n; ++i)
        {
            sum1 += x[i]*x[i];
            sum2 += cos(c*x[i]);
        }
    *f=-a*exp(-b*sqrt((1.0/n)*sum1)) - exp((1.0/n)*sum2) + a + exp(1.0);
    //Calculating derivatives
    int j;
    for (j = 0; j < (int) n; ++j)
        df[j] = 0; //Initializing to 0.
            df[j] += a*b*x[j]*exp(-(1.0/n)*b*sqrt(n*sum1))/sqrt (n*sum1);
            df[j] += -1.0/n*sin(c*x[j])*exp(1.0/n*sum2);
        }
```

```
|
49
51 }
//Example of using the algorithm.
double TestAckley()
{
    //Generate random starting guess
    unsigned int iseed = (unsigned int) time(NULL);
    srand (iseed);
    //Number of inputs to n, number of max iterations
    int n = 5000;
    int maxiters = 10000;
    double x[n];
    int i;
    //Randomly generate numbers
    for (i = 0; i < n; ++i) x[i] = (rand()%600-300)/100.0;
    //Define array with params
    double pi = 3.141592654;
    double p[] = {20, 0.2, 2*pi, (double) n};
    //Setting options
    double opts[] = {1.0, 1e-4, 1e-8, maxiters, 0};
    //The function shall be called on the function, using x as starting guess,
    //with n values, opts shall be used for options, no initial approximation of
        inverse Hessian,
    double xinfo[n*maxiters];
    double t1 = opti_get_time();
    int ucminfr = opti_ucminf(ackley, x, n, opts, NULL, NULL, NULL, NULL, (void
        *) p);
    double t2 = opti_get_time();
    double f, df[n];
    ackley(x, &f, df, (void*) p);
    printf("%f\n",f);
    return t2 - t1;
}
#endif /* ACKLEY_H_ * /
```


## C. 7 Zakharov

## C.7.1 MATLAB test

```
    tic,
    yin = ones(1000,1);
    y = ucminf(@zakh2,yin, [1 1e-10, 1e-10, 1000]);
    [f g] = zakh2(y);
    f, h = norm(g),
    t1(i) = toc;
end
time1 = sum(t1)/10;
for i = 1:10
    tic,
    xin = ones(1000,1);
    x = fminunc(@zakh,xin);
    t2(i) = toc;
end
time2 = sum(t2)/10;
t1, time1, t2, time2
```


## C.7.2 minlbfgs test

```
#include <stdlib.h>
#include <stdio.h>
#include <cmath>
#include "ap.h"
#include "minlbfgs.h"
using namespace std;
//Needs to be put into alltests!
#include <time.h>
#include <sys/time.h>
#ifdef __MACH__ //If on a Mac, use Mach libraries
#include <mach/clock.h>
#include <mach/mach.h>
#endif //___MACH__
double get_time()
{
    struct timespec ts;
#ifdef __MACH__ // OS X does not have clock_gettime, use clock_get_time
        clock_serv_t cclock;
        mach_timespec_t mts;
        host_get_clock_service(mach_host_self(), CALENDAR_CLOCK, &cclock);
        clock_get_time(cclock, &mts);
        mach_port_deallocate(mach_task_self(), cclock);
        ts.tv_sec = mts.tv_sec;
        ts.tv_nsec = mts.tv_nsec;
#else
#ifdef CLOCK_MONOTONIC
        clock_gettime(CLOCK_MONOTONIC, &ts);
#else
    clock_gettime(CLOCK_REALTIME, &ts);
#endif
#endif
    return (double) ts.tv_sec + (double) ts.tv_nsec * 1e-9;
}
```

```
void zakharov(double* x, double* f, double* df)
{
    int n, i;
    n = 1000;
    *f = 0;
    double fpart23 = 0;
    for (i = 0; i < n; ++i)
    {
        *f += x[i]*x[i];
        fpart23 += 0.5*i*x[i];
    }
    *f += pow((fpart23),2) + pow((fpart23),4);
}
/ / =======================
int main(int argc, char **argv)
{
    int n = 1000;
    int m = 1;
    minlbfgsstate state;
    minlbfgsreport rep;
    ap::real_1d_array s;
    double x[n];
    double timet = 0;
    s.setlength(n);
    //f and g
    double f;
    double g[n];
    for (int i = 0; i < 10; ++i)
    {
    for (int k = 0; k < n; ++k) s(k) = 1;
    double t1 = get_time();
    minlbfgscreate(n, m, s, state);
    minlbfgssetcond(state, 1e-10, 1e-10, 1e-10, 1000);
    while(minlbfgsiteration(state))
    whi
        if( state.needfg )
        {
            for (int k = 0; k < n; ++k)
                    x[k] = state.x(k);
            zakharov(x, &f, g);
            state.f = f;
            for (int k = 0; k < n; ++k)
            state.g(k) = g[k];
        }
    }
    minlbfgsresults(state, s, rep);
```

```
103
    double t2 = get_time();
    timet += t2 - t1;
    printf("Solve time: %f\n", t2 - t1);
    }
    printf("Average solve time: %f\n", timet /= 10);
    return 0;
```


## C.7.3 libopti test

```
/*
* zakharov.h
* Created on: Aug 18, 2012
    * Author: christian
*/
#ifndef ZAKHAROV_H_
#define ZAKHAROV_H_
#include <math.h>
#include <stddef.h>
#include <stdio.h>
void zakharov(double* x, double* f, double* df, void *p)
{
    int n, i;
    n = *((int*) p);
    *f = 0;
    double fpart23 = 0;
    for (i = 0; i < n; ++i)
    { *f += x[i]*x[i];
        fpart23 += 0.5*i*x[i];
    }
    *f += pow((fpart23),2) + pow((fpart23),4);
}
//Example of using the algorithm.
double TestZakharov()
{
    //Number of inputs, number of max iterations
    int n = 10, maxiters = 1000;
    //Setting options.
```

```
    // \Delta - Initial value for largest stepsize used by the
        linesearching.
            tolg - The value which the norm of g}\mathrm{ is under when the
            1st order KKT conditions are met.
                    tolx - If the stepsize is less than tolx*(tolx +
        opti_norm(x, n, 2)), stop.
            maxeval - The maximum number of tolerable iterations
        before stopping.
                            findiffh - Used in the finite difference approximation for
        fun(). If set to 0, df is expected.
                            Warning: Using findiffh = 0 and not supplying g
        in fun WILL result in errors.
    // Default: 1, 1e-4, 1e-8, 100, 0
    double opts[] = {1.0, 1e-8, 1e-8, maxiters, 0.0001};
    //The function shall be called on the function, using x as starting guess,
    //with n values, opts shall be used for options, no initial approximation
        of inverse Hessian,
    double perfinfo[maxiters*6];
    double xinfo[n*maxiters];
    //Starting guess 1
    double x[n];
    int i; for (i = 0; i < n; ++i) x[i] = 1;
    double t1 = opti_get_time();
    int ucminfr = opti_ucminf(zakharov, x, n, opts, NULL, NULL, perfinfo,
        xinfo, (void*) &n);
    double t2 = opti_get_time();
    double df[2], f;
    zakharov(x, &f, df, (void*) &n);
    printf("sizex = %f\n", x[5]);
    return t2 - t1;
#endif /* ZAKHAROV_H_ */
```

\}

## C. 8 Plot Ackley performance

```
clear all
load testackley/am.txt
load testackley/\Delta.txt
load testackley/evals.txt
load testackley/finalslope.txt
load testackley/fun.txt
load testackley/ng.txt
subplot (3,2,1);
plot(1:length(am),am);
xlabel iteration, ylabel alpha
subplot (3,2,2);
plot (1:length(am),\Delta);
xlabel iteration, ylabel \Delta,
subplot (3,2,3);
```

```
plot(1:length(am),evals);
xlabel iteration, ylabel evals,
subplot(3,2,4);
plot(1:length(am),finalslope);
xlabel iteration, ylabel 'final slope',
subplot(3,2,5);
plot(1:length(am),fun);
xlabel iteration, ylabel f,
subplot(3,2,6);
plot(1:length(am),ng);
xlabel iteration, ylabel norm(g),
```


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    $2(1.000000,0.999999)$

