### 5.2 Numerical methods for $N$-dimensional nonlinear problems

For $N$ dimensional problems there are no practical analogs of the bisection method. However, Newton's method can easily be extended to $N$ dimensional problems. An approximate Newton's method similar to the secant method and based on finite difference-type approximations also exists.

### 5.2.1 The $N$-dimensional Newton's Method

Let $F: \mathbb{R}^{N} \rightarrow \mathbb{R}^{N}$ given by $F(x)=\left(F_{i}(x)\right)_{i=1: N}$, where $F_{i}: \mathbb{R}^{N} \rightarrow \mathbb{R}$. Assume that all the partial order derivatives of the functions $F_{i}(x), i=1: N$, are continuous. We want to solve the nonlinear $N$-dimensional problem

$$
F(x)=0 .
$$

Recall from (1.40) that the gradient $D F(x)$ of $F(x)$ is an $N \times N$ matrix:

$$
D F(x)=\left(\begin{array}{cccc}
\frac{\partial F_{1}}{\partial x_{1}}(x) & \frac{\partial F_{1}}{\partial x_{2}}(x) & \ldots & \frac{\partial F_{1}}{\partial x_{N}}(x) \\
\frac{\partial F_{2}}{\partial x_{1}}(x) & \frac{\partial F_{2}}{\partial x_{2}}(x) & \ldots & \frac{\partial F_{2}}{\partial x_{N}}(x) \\
\vdots & \vdots & \vdots & \vdots \\
\frac{\partial F_{N}}{\partial x_{1}}(x) & \frac{\partial F_{N}}{\partial x_{2}}(x) & \ldots & \frac{\partial F_{N}}{\partial x_{N}}(x)
\end{array}\right) .
$$

The recursion for Newton's method follows from the linear Taylor expansion of $F(x)$, i.e.,

$$
\begin{equation*}
F(x) \approx F\left(x_{k}\right)+D F\left(x_{k}\right)\left(x-x_{k}\right) ; \tag{5.18}
\end{equation*}
$$

cf. (6.29) for $a=x_{k}$. Here, $D F\left(x_{k}\right)\left(x-x_{k}\right)$ is a matrix-vector multiplication. Let $x=x_{k+1}$ in (5.18). Approximating $F\left(x_{k+1}\right)$ by 0 (which happens in the limit, if convergence to a solution for $F(x)=0$ is achieved), we find that

$$
\begin{equation*}
0 \approx F\left(x_{k}\right)+D F\left(x_{k}\right)\left(x_{k+1}-x_{k}\right) \tag{5.19}
\end{equation*}
$$

Changing (5.19) into an equality and solving for $x_{k+1}$, we obtain the following recursion for Newton's method for $N$ dimensional problems:

$$
\begin{equation*}
x_{k+1}=x_{k}-\left(D F\left(x_{k}\right)\right)^{-1} F\left(x_{k}\right), \quad \forall k \geq 0 \tag{5.20}
\end{equation*}
$$

At each step, the vector $\left(D F\left(x_{k}\right)\right)^{-1} F\left(x_{k}\right)$ must be computed. In practice, the inverse matrix $\left(D F\left(x_{k}\right)\right)^{-1}$ is never explicitely computed, since this would be very expensive computationally. Instead, we note that computing the vector $v_{k}=$ $\left(D F\left(x_{k}\right)\right)^{-1} F\left(x_{k}\right)$ is equivalent to solving the linear system

$$
D F\left(x_{k}\right) v_{k}=F\left(x_{k}\right) .
$$

This is done using numerical linear algebra methods, e.g., by computing the LU decomposition factors of the matrix $D F\left(x_{k}\right)$ and then doing a forward and a backward substitution.

It is not our goal here to discuss such methods; see [39] for details on numerical linear algebra methods. We subsequently assume that a routine for solving linear systems called solve_linear_system exists such that, given a nonsingular square matrix $A$ and a vector $b$, the vector

$$
x=\text { solve_linear_system }(A, b)
$$

is the unique solution of the linear system $A x=b$.
The vector $v_{k}=\left(D F\left(x_{k}\right)\right)^{-1} F\left(x_{k}\right)$ can then be computed as

$$
v_{k}=\text { solve_linear_system }\left(D F\left(x_{k}\right), F\left(x_{k}\right)\right)
$$

and recursion (5.20) can be written as

$$
x_{k+1}=x_{k}-\text { solve_linear_system }\left(D F\left(x_{k}\right), F\left(x_{k}\right)\right), \quad \forall k \geq 0 .
$$

The $N$-dimensional Newton's method iteration is stopped and convergence to a solution to the problem $F(x)=0$ is declared when the following two conditions are satisfied:

$$
\begin{equation*}
\left\|F\left(x_{n e w}\right)\right\| \leq \text { tol_approx and }\left\|x_{\text {new }}-x_{\text {old }}\right\| \leq \text { tol_consec, } \tag{5.21}
\end{equation*}
$$

where $x_{\text {new }}$ is the most recent value generated by Newton's method and $x_{\text {old }}$ is the value previously computed by the algorithm. Possible choices for the tolerance factors are tol_consec $=10^{-6}$ and tol_approx $=10^{-9}$; see the pseudocode from Table 5.4 for more details.

Table 5.4: Pseudocode for the $N$-dimensional Newton's Method

```
Input:
\(x_{0}=\) initial guess
\(F(x)=\) given function
tol_approx \(=\) largest admissible value of \(\|F(x)\|\) when solution is found
tol_consec \(=\) largest admissible distance between
        two consecutive approximations when solution is found
Output:
\(x_{\text {new }}=\) approximate solution for \(f(x)=0\)
\(x_{n e w}=x_{0} ; x_{\text {old }}=x_{0}-1\)
while \(\left(\left\|F\left(x_{\text {new }}\right)\right\|>\right.\) tol_approx \()\) or \(\left(\left\|x_{\text {new }}-x_{\text {old }}\right\|>\right.\) tol_consec \()\)
    \(x_{\text {old }}=x_{\text {new }}\)
    compute \(D F\left(x_{\text {old }}\right)\)
    \(x_{\text {new }}=x_{\text {old }}-\) solve_linear_system \(\left(D F\left(x_{\text {old }}\right), F\left(x_{\text {old }}\right)\right)\)
end
```

Note that $\|\cdot\|$ represents the Euclidean norm, i.e., $\|v\|=\left(\sum_{i=1}^{N}\left|v_{i}\right|^{2}\right)^{1 / 2}$, where $v=\left(v_{i}\right)_{i=1: N}$ is a vector in $\mathbb{R}^{N}$.

As was the case for the one-dimensional version, the $N$-dimensional Newton's method converges quadratically if certain conditions are satisfied.

Theorem 5.3. Let $x^{*}$ be a solution of $F(x)=0$, where $F(x)$ is a function with continuous second order partial derivatives. If $D F\left(x^{*}\right)$ is a nonsingular matrix, and if $x_{0}$ is close enough to $x^{*}$, then Newton's method converges quadratically, i.e., there exists $M>0$ and $n_{M}$ a positive integer such that

$$
\frac{\left\|x_{k+1}-x^{*}\right\|}{\left\|x_{k}-x^{*}\right\|^{2}}<M, \quad \forall k \geq n_{M}
$$

Example: Use Newton's method to solve $F(x)=0$, for

$$
F(x)=\left(\begin{array}{c}
x_{1}^{3}+2 x_{1} x_{2}+x_{3}^{2}-x_{2} x_{3}+9 \\
2 x_{1}^{2}+2 x_{1} x_{2}^{2}+x_{2}^{3} x_{3}^{2}-x_{2}^{2} x_{3}-2 \\
x_{1} x_{2} x_{3}+x_{1}^{3}-x_{3}^{2}-x_{1} x_{2}^{2}-4
\end{array}\right)
$$

Answer: Note that

$$
D F(x)=\left(\begin{array}{ccc}
3 x_{1}^{2}+2 x_{2} & 2 x_{1}-x_{3} & 2 x_{3}-x_{2} \\
4 x_{1}+2 x_{2}^{2} & 4 x_{1} x_{2}+3 x_{2}^{2} x_{3}^{2}-2 x_{2} x_{3} & 2 x_{2}^{3} x_{3}-x_{2}^{2} \\
x_{2} x_{3}+3 x_{1}^{2}-x_{2}^{2} & x_{1} x_{3}-2 x_{1} x_{2} & x_{1} x_{2}-2 x_{3}
\end{array}\right) .
$$

We use the algorithm from Table 5.4 with tol_consec $=10^{-6}$ and tol_approx $=10^{-9}$. For the initial guess

$$
x_{0}=\left(\begin{array}{l}
1 \\
2 \\
3
\end{array}\right), \text { the solution } x^{*}=\left(\begin{array}{c}
-1.690550759854953 \\
1.983107242868416 \\
-0.884558078475291
\end{array}\right)
$$

is found after 9 iterations.
For the initial guess

$$
x_{0}=\left(\begin{array}{l}
2 \\
2 \\
2
\end{array}\right), \text { the solution } x^{*}=\left(\begin{array}{c}
-1 \\
3 \\
1
\end{array}\right)
$$

is found after 40 iterations.

### 5.2.2 The Approximate Newton's Method

In many instances, it is not possible (or efficient) to find a closed formula for the matrix $D F(x)$ which is needed for Newton's method; cf. (5.20). In these cases, finite difference approximations can be used to estimate each entry of $D F(x)$. The resulting method is called the Approximate Newton's Method.

The entry of $D F(x)$ on the position $(i, j)$, i.e., $\frac{\partial F_{i}}{\partial x_{j}}(x)$, is estimated using forward finite differences approximations (7.2) as

$$
\begin{equation*}
\frac{\partial F_{i}}{\partial x_{j}}(x) \approx \Delta_{j} F_{i}(x)=\frac{F_{i}\left(x+h e_{j}\right)-F_{i}(x)}{h} \tag{5.22}
\end{equation*}
$$

