## Appendix A

## Tensor calculus

## A. 1 Tensors

The basis for expressing elastic equations is Euclidian 3-dimensional space, i.e., $\mathbb{R}^{3}$ with the Euclidian inner product. Vectors from $\mathbb{R}^{3}$ are denoted by bold lower case letters, e.g. $\mathbf{a}, \mathbf{b}$, and are also known as first-order tensors, or 1 -tensors. We assume that an inner product on $\mathbb{R}^{3}$ is given, and that it is denoted by $\mathbf{a} \cdot \mathbf{b}$ for $\mathbf{a}$ and $\mathbf{b} \in \mathbb{R}^{3}$.

If we have a basis $\left\{\mathbf{a}_{1}, \mathbf{a}_{2}, \mathbf{a}_{3}\right\}$ for $\mathbb{R}^{3}$, then we can determine the components of a vector with regard to that basis using the dual basis. The dual of $\left\{\mathbf{a}_{1}, \mathbf{a}_{2}, \mathbf{a}_{3}\right\}$ is denoted $\left\{\mathbf{a}^{1}, \boldsymbol{a}^{2}, \boldsymbol{a}^{3}\right\}$. It is determined uniquely by

$$
x=\sum_{i}\left(a^{i} \cdot x\right) a_{i}, \quad x \in \mathbb{R}^{3}
$$

A basis is called orthonormal if it is equal to its own dual.
The set of linear mappings from $\mathbb{R}^{3}$ to $\mathbb{R}^{3}$ is a 9-dimensional space, denoted by $\operatorname{Lin}\left(\mathbb{R}^{3}, \mathbb{R}^{3}\right)$, or Lin for short. The elements of Lin are also known as second order tensors, and are printed in bold upper case, e.g. T and E. The identity tensor is denoted by I.

When we evaluate a linear mapping $\boldsymbol{A}$ in a point $\boldsymbol{x}$, we write $\boldsymbol{A} \cdot \mathbf{x}$. The product $\boldsymbol{A} \cdot \mathbf{B}$ of two 2 -tensors $\boldsymbol{A}$ and $\mathbf{B}$ is the 2-tensor defined by

$$
(\mathbf{A} \cdot \mathbf{B}) \cdot \boldsymbol{x}=\mathbf{A} \cdot(\mathbf{B} \cdot \boldsymbol{x}) .
$$

The transpose (or adjoint) $\boldsymbol{A}^{*}$ of $\boldsymbol{A}$ is the unique tensor satisfying

$$
\begin{equation*}
\mathbf{u} \cdot(\boldsymbol{A} \cdot \boldsymbol{v})=\left(\boldsymbol{A}^{*} \cdot \mathbf{u}\right) \cdot \boldsymbol{v} \tag{A.1}
\end{equation*}
$$

For notational convenience, we set $\boldsymbol{v} \cdot \boldsymbol{A}:=\boldsymbol{A}^{*} \cdot \boldsymbol{v}$. The transpose is a linear operation on 2 -tensors. A tensor is called symmetric if $\boldsymbol{A}^{*}=\boldsymbol{A}$.

A function taking $\mathbf{u}$ to $\mathbf{u} \cdot \boldsymbol{A} \cdot \mathbf{u}$ is called a quadratic form. If $\mathbf{u} \cdot \boldsymbol{A} \cdot \mathbf{u}>0$ for all $\mathbf{u} \neq 0$, then the quadratic form is positive definite, and if $\mathbf{u} \cdot \boldsymbol{A} \cdot \mathbf{u} \geq 0$, then it is positive semidefinite. Negative definite and negative semidefinite are defined similarly.

If $\mathbf{a}$ and $\mathbf{b}$ are 1 -tensors, then we can construct a linear mapping from $\mathbf{a}$ and $\mathbf{b}$ by setting

$$
\begin{equation*}
(\mathbf{a} \otimes \mathbf{b})(\mathbf{x})=(\mathbf{b} \cdot \mathbf{x}) \mathbf{a}, \quad \mathbf{a}, \mathbf{b} \in \mathbb{R}^{3} \tag{A.2}
\end{equation*}
$$

This mapping is called a dyadic product, dyad or tensor-product. To illustrate the meaning, when $\left\{\mathbf{a}_{1}, \mathbf{a}_{2}, \mathbf{a}_{3}\right\}$ and $\left\{\mathbf{b}_{1}, \mathbf{b}_{2}, \mathbf{b}_{3}\right\}$ are orthonormal bases, then the dyad $\left(\mathbf{a}_{2} \otimes \mathbf{b}_{1}\right)$ applied to $\boldsymbol{x}$ takes the magnitude of the $\mathbf{b}_{1}$ component of $\boldsymbol{x}$, and maps that component to $\boldsymbol{a}_{2}$. If $\left\{\boldsymbol{a}_{1}, \mathbf{a}_{2}, \boldsymbol{a}_{3}\right\}$ and $\left\{\mathbf{b}_{1}, \mathbf{b}_{2}, \mathbf{b}_{3}\right\}$ are bases of $\mathbb{R}^{3}$, then set of dyads given by $\left\{\mathbf{a}_{\boldsymbol{i}} \otimes \mathbf{b}_{\mathfrak{j}} \mid \boldsymbol{i}, \mathfrak{j}=1,2,3\right\}$ has nine elements, and it forms a basis of the linear mappings of $\mathbb{R}^{3}$. Since these dyads form a basis, we may also use Equation (A.2) as a definition for function application. Higher order tensor products (3-tensors and 4tensors) may also defined, to represent mappings between $\mathbb{R}^{3}$ and Lin and between Lin and Lin.

We can also express matrix multiplication using dyads. Let $\boldsymbol{A}: \mathbf{a} \otimes \mathbf{b}$ and $\mathbf{B}:=\mathbf{c} \otimes \mathbf{d}$, then we have

$$
(\mathbf{A} \cdot \mathbf{B})(\mathbf{x})=(\mathbf{a} \otimes \mathbf{b}) \mathbf{c}(\mathbf{d} \cdot \mathbf{x})=(\mathbf{b} \cdot \mathbf{c})(\mathbf{a} \otimes \mathbf{d})(\mathbf{x})
$$

Since the dyads form a base of Lin, we may also define linear operations in Lin in terms of dyads. For instance, the transpose or adjoint can be defined as

$$
(\mathbf{a} \otimes \mathbf{b})^{*}=\mathbf{b} \otimes \mathbf{a}
$$

The trace is a linear functional on Lin: it takes a linear mapping, and returns a number. It can be defined in terms of dyads

$$
\begin{equation*}
\operatorname{trace}(\mathbf{a} \otimes \mathbf{b})=\mathbf{a} \cdot \mathbf{b} \tag{A.3}
\end{equation*}
$$

With the help of the trace operator we can define an inner product on Lin. The inner product between $\boldsymbol{A}$ and $\mathbf{B}$ is denoted by $\boldsymbol{A}: \mathbf{B}$, and is given by

$$
\begin{equation*}
\mathbf{A}: \mathbf{B}=\operatorname{trace}\left(\mathbf{B}^{*} \cdot \mathbf{A}\right) \tag{A.4}
\end{equation*}
$$

We have $\operatorname{trace}(\boldsymbol{A})=\boldsymbol{A}: \mathbf{I}$. When 2-tensors are represented by matrices, then the trace corresponds to the sum of the diagonal elements. The inner product on Lin corresponds to the Euclidian inner product on $\mathbb{R}^{3 \times 3}$.

By use of tensor products, we may extend these inner products to tensor products between arbitrary dimensions. The inner product of a $k$ and l-tensor product

$$
\left(\mathbf{a}_{1} \otimes \cdots \otimes \mathbf{a}_{k}\right) \cdot\left(\mathbf{b}_{1} \otimes \cdots \otimes \mathbf{b}_{l}\right)=\left(\mathbf{a}_{k} \cdot \mathbf{b}_{1}\right)\left(\mathbf{a}_{1} \otimes \cdots \otimes \mathbf{a}_{\mathrm{k}-1}\right) \otimes\left(\mathbf{b}_{2} \otimes \cdots \otimes \mathbf{b}_{l}\right)
$$

Similarly, we may extend the inner product for two tensors to arbitrary dimensions.
$\left(\mathbf{a}_{1} \otimes \cdots \otimes \mathbf{a}_{\mathrm{k}}\right):\left(\mathbf{b}_{1} \otimes \cdots \otimes \mathbf{b}_{\mathrm{l}}\right)=\left(\mathbf{a}_{\mathrm{k}-1} \cdot \mathbf{b}_{1}\right)\left(\mathbf{a}_{\mathrm{k}} \cdot \mathbf{b}_{2}\right)\left(\mathbf{a}_{1} \otimes \cdots \otimes \mathbf{a}_{\mathrm{k}-2}\right) \otimes\left(\mathbf{b}_{3} \otimes \cdots \otimes \mathbf{b}_{\mathrm{l}}\right)$.
The expression

$$
\mathbf{a} \cdot(\mathbf{b} \times \mathbf{c})
$$

measures the oriented volume of the parallelepiped spanned by $\mathbf{a}, \mathbf{b}$ and $\mathbf{c}$. It is called the scalar triple-product of vectors $\mathbf{a}, \mathbf{b}$ and $\mathbf{c}$. The determinant of a mapping $\boldsymbol{A}$ from

Lin measures how the volume of a parallelepiped changes when it transformed through $\boldsymbol{A}$. This definition is independent of the parallelepiped used. In other words, given an arbitrary set of independent vectors $\mathbf{a}, \mathbf{b}, \mathbf{c}$, then the determinant is uniquely defined by

$$
\begin{equation*}
\operatorname{det} \mathbf{A}=\frac{(\mathbf{A} \mathbf{a}) \cdot(\mathbf{A} \mathbf{b} \times(\mathbf{A} \mathbf{c}))}{\mathbf{a} \cdot(\mathbf{b} \times \mathbf{c})} \tag{A.5}
\end{equation*}
$$

The determinant satisfies $\operatorname{det}(\boldsymbol{A} \cdot \mathbf{B})=\operatorname{det} \boldsymbol{A} \operatorname{det} \mathbf{B}$, and hence $\operatorname{det}\left(\boldsymbol{A}^{-1}\right)=1 / \operatorname{det} \boldsymbol{A}$, if $\boldsymbol{A}^{-1}$ exists. It follows that $\operatorname{det}\left(\boldsymbol{X} \boldsymbol{A} \boldsymbol{X}^{-1}\right)=\operatorname{det}(\boldsymbol{A})$ : the determinant is invariant under a change of basis.

A vector $\boldsymbol{v}$ is called an eigenvector of $\boldsymbol{A}$ if there is a number $\lambda$, the eigenvalue, such that

$$
A v=\lambda c
$$

Eigenvalues are given by the roots of the characteristic polynomial. The characteristic polynomial of a 2 -tensor $\boldsymbol{A}$ is defined as $\operatorname{det}(\boldsymbol{A}-\lambda \mathbf{I})$. We can expand this expression as a polynomial, thus obtaining

$$
\operatorname{det}(\mathbf{A}-\lambda \mathbf{I})=-\lambda^{3}+\iota_{1} \lambda^{2}-\iota_{2} \lambda+\iota_{3} .
$$

The coefficients $\iota_{1}, \iota_{2}$ and $\iota_{3}$ in this expansion are called invariants of $\boldsymbol{A}$. Since the determinant is invariant under change of basis, the invariants also are. If $\lambda_{1}, \lambda_{2}$ and $\lambda_{3}$ are the eigenvalues of $\boldsymbol{A}$, then we have

$$
\begin{gather*}
\iota_{1}(\boldsymbol{A})=\lambda_{1}+\lambda_{2}+\lambda_{3} \\
\iota_{2}(\boldsymbol{A})=\lambda_{1} \lambda_{2}+\lambda_{2} \lambda_{3}+\lambda_{3} \lambda_{1}  \tag{A.6}\\
\iota_{3}(\boldsymbol{A})=\lambda_{1} \lambda_{2} \lambda_{3} .
\end{gather*}
$$

The invariants can also be determined directly from $\boldsymbol{A}$. We have

$$
\begin{aligned}
& \iota_{1}(\boldsymbol{A})=\operatorname{trace}(\boldsymbol{A}) \\
& \iota_{2}(\boldsymbol{A})=\frac{1}{2}\left((\operatorname{trace} \boldsymbol{A})^{2}-\operatorname{trace}\left(\boldsymbol{A}^{*} \cdot \boldsymbol{A}\right)\right), \\
& \iota_{3}(\boldsymbol{A})=\operatorname{det} \boldsymbol{A} .
\end{aligned}
$$

## A. 2 Tensor calculus

A function $f: \mathbb{R} \rightarrow \mathbb{R}$ is differentiable in $x \in \mathbb{R}$, when there is a number $d(x)$ and a function $r(x, h)$, such that

$$
f(x+h)=f(x)+d(x) h+r(x, h), \quad r(x, h)=o(h) \text { when } h \rightarrow 0 .
$$

In other words, $f$ is differentiable in $x$ if it may be linearly approximated in a neighborhood of $x$. The function $d(x)$ is the derivative of $f$ in $x$, also denoted by $\frac{d f}{d x}$.

This definition can be generalized to higher dimensions. Let $\mathcal{V}$ and $\mathcal{W}$ be finitedimensional vector spaces. A function $\mathrm{F}: \mathcal{V} \rightarrow \mathcal{W}$, is called Fréchet-differentiable in $\mathcal{V}$ if there is a linear mapping $L: \mathcal{V} \rightarrow \mathcal{W}$ such that

$$
\mathrm{F}(v+\mathrm{h})=\mathrm{F}(v)+\mathrm{L}(\mathrm{~h})+\mathrm{o}(\mathrm{~h}), \quad \mathrm{h} \in \mathcal{V} .
$$

Since L is a linear mapping, we may write it as some product of some D in the tensor product space of $\mathcal{V}$ and $\mathcal{W}$. This representant D of the mapping L is called the derivative.

For example, if a function $f$ maps vectors from $\mathbb{R}^{3}$ to numbers, then it is differentiable in $x$ if there exists functions $f_{x}$ and $r$, such that

$$
f(x+h)=f(x)+f_{x}(x) \cdot h+r(x, h)
$$

and $r(\boldsymbol{x}, \mathbf{h})=\mathbf{o}(\|\mathbf{h}\|)$. The mapping $\mathbf{h} \mapsto \mathrm{f}_{\boldsymbol{x}}(\boldsymbol{x}) \cdot \mathbf{h}$ is a linear mapping. The function can be represented as an inner product of $\mathbf{f}_{\boldsymbol{x}}(\boldsymbol{x})$ and the argument. Hence, $\boldsymbol{f}_{\boldsymbol{x}}(\boldsymbol{x})$ is is called the derivative or gradient of $f$. It is denoted as $\frac{\partial f}{\partial x}$. Other notations include grad $f$ or $\nabla \mathrm{f}$.

If $f: \operatorname{Lin} \rightarrow \mathbb{R}$ is a differentiable function taking linear mappings to scalars, then there exists a function $r$ and $\partial f / \partial \mathcal{A}: \operatorname{Lin} \rightarrow \mathbb{R}$, such that

$$
f(\boldsymbol{A}+\mathbf{H})=\mathrm{f}(\boldsymbol{A})+\frac{\partial \mathrm{f}}{\partial \boldsymbol{A}}: \mathbf{H}+\mathrm{r}(\boldsymbol{A}, \mathbf{H}), \quad \boldsymbol{A} \in \operatorname{Lin}
$$

where $r(\boldsymbol{A}, \mathbf{H}) /\|\mathbf{H}\| \rightarrow 0$ when $\mathbf{H} \rightarrow 0$. The derivative $\frac{\partial f(\boldsymbol{A})}{\partial \boldsymbol{A}}$ is also denoted by $\mathrm{f}_{\boldsymbol{A}}(\boldsymbol{A})$.
Some derivatives of standard functions are given here.

$$
\begin{gathered}
\frac{\partial \operatorname{trace}(\mathbf{C})}{\partial \mathbf{C}}=\mathbf{I} \\
\frac{\partial \operatorname{det}(\mathbf{C})}{\partial \mathbf{C}}=\operatorname{det} \mathbf{C} \mathbf{C}^{-*} \\
\frac{\partial \iota_{2}(\mathbf{C})}{\partial \mathbf{C}}=\operatorname{trace}(\mathbf{C}) \mathbf{I}-\mathbf{C}
\end{gathered}
$$

The inverse of a 2-tensor is another 2-tensor, so taking inverses is a function from Lin to Lin. Its derivative is a linear function from Lin to Lin , which may be represented as a 4-tensor. To avoid the hassle of representing 4-tensors, we simply give the derivative applied to some $\mathbf{H} \in \operatorname{Lin}$ :

$$
\frac{\partial \mathbf{C}^{-1}}{\partial \mathbf{C}}: \mathbf{H}=-\mathbf{C}^{-1} \cdot \mathbf{H} \cdot \mathbf{C}^{-1}
$$

We mention one differential operator that we shall encounter further, the divergence. The divergence of a vector field $\mathbf{f}: \mathbb{R}^{3} \rightarrow \mathbb{R}^{3}$ is defined by

$$
\operatorname{div} f=\operatorname{trace}(\partial \mathbf{f} / \partial \mathbf{x})
$$

The divergence of a tensor field $\mathbf{T}$ is defined by

$$
\operatorname{div} \mathbf{T}=\partial \mathbf{T} / \partial x: \mathbf{I}
$$

In one dimension, the value of an integral over an interval of a continuous function is given by the values of its primitive at the boundaries of that interval. A similar theorem holds in higher dimensions. If $\Psi$ is a tensor valued function, and continuously
differentiable on its domain $\Omega$, and continuous on the closure of $\Omega$, then

$$
\int_{\Omega} \partial \Psi / \partial \boldsymbol{x} \mathrm{d} v(\boldsymbol{x})=\int_{\partial \Omega} \Psi \otimes \boldsymbol{n}(\boldsymbol{x}) \mathrm{da}(\mathbf{x})
$$

where $\boldsymbol{n}$ is the outward pointing normal on $\partial \Omega$. This theorem can applied to tensors of different order, e.g. the divergence theorem. One form that we employ is

$$
\begin{equation*}
\int_{\mathcal{B}} \operatorname{div} \mathbf{T} \mathrm{d} v(\boldsymbol{x})=\int_{\partial \mathcal{B}} \mathbf{T} \cdot \mathbf{n} \mathrm{d} v(\boldsymbol{x}) . \tag{A.7}
\end{equation*}
$$

