# On the polar decomposition of the deformation gradient tensor

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The deformation gradient tensor  $\mathbf{F}$  can map a line element in the initial state  $\mathbf{dX}$  to the corresponding line element (in terms of size and orientation) in the final state  $\mathbf{dx}$ , which is expressable as:

$$d\mathbf{x} = \mathbf{F}d\mathbf{X}$$

The polar decomposition of the deformation gradient tensor produces:

$$F = QU = VQ$$

Where  $\mathbf{Q}$  is a rotation tensor, and  $\mathbf{U}$  and  $\mathbf{V}$  are known as the the right and left stretch tensors respectively. Hence the deformation event due to  $\mathbf{F}$  can be thought of as a stretching followed by a rotation ( $\mathbf{Q}\mathbf{U}$ ) or equivalently a rotation followed by a stretching ( $\mathbf{V}\mathbf{Q}$ ). Which in equation form can be presented as:

$$d\mathbf{x} = \mathbf{F} d\mathbf{X}$$

Although the eigen vectors for **U** and **V** differ, they share the same eigen values, i.e. the principal stretches  $\lambda_1$ ,  $\lambda_2$ , and  $\lambda_3$ .

Obtaining the rotation tensor  $\mathbf{Q}$ , and the stretch tensors  $\mathbf{U}$  and  $\mathbf{V}$ , as well as their eigen vectors and eigen values, can be conveniently achieved through the use of the singular value decomposition of  $\mathbf{F}$ , which is given by:

$$F = W\Sigma R$$

Here **W** and **R** are rotation tensors, and  $\Sigma$  is the singular value matrix. This enables the computation of the rotation tensor **Q** through:

$$\mathbf{Q} = \mathbf{W}\mathbf{R}^\top$$

and the computation of the right stretch tensor **U** through:

$$\mathbf{U} = \mathbf{R}^{\mathsf{T}} \mathbf{F} = \mathbf{R} \mathbf{\Sigma} \mathbf{R}^{\mathsf{T}}$$

and the computation of the left stretch tensor  $\mathbf{V}$  through:

$$\mathbf{V} = \mathbf{F} \mathbf{R}^{\top} = \mathbf{W} \mathbf{\Sigma} \mathbf{W}^{\top}$$

The eigenvalues or principal stretches are obtained from the singular value matrix  $\Sigma$  through:

$$\lambda_i = \Sigma_{ii}$$

The eigenvectors for the right stretch tensor  $\mathbf{U}$  (or more formally of  $\mathbf{C} = \mathbf{F}^{\top}\mathbf{F}$  but with which they coincide) are obtained from the columns of  $\mathbf{R}$ :

$$\mathbf{n_j} = \sum_{i=1}^3 R_{ij} \mathbf{e_i}$$

Similarly the eigenvectors for the left stretch tensor  $\mathbf{V}$  (or more formally of  $\mathbf{B} = \mathbf{F}\mathbf{F}^{\top}$  but with which they coincide) are obtained from the columns of  $\mathbf{W}$ :

$$\mathbf{m_j} = \sum_{i=1}^3 W_{ij} \mathbf{e_i}$$

### Numerical implementation

Setting up required packages. We need some here for rotations and linear algebra.

```
1 # Loading required packages
2 using Rotations; using LinearAlgebra;
```

A simulated deformation gradient tensor  $\mathbf{F}$  is now created. This is done by first defining some known principal stretches  $\lambda_i$ , using this to define a known right stretch tensor  $\mathbf{U}$ , and finally rotating this stretch tensor using a rotation matrix  $\mathbf{Q}$  to obtain  $\mathbf{F}$  from:

$$\mathbf{F} = \mathbf{Q}\mathbf{U}$$

Let's first define the principal stretches  $\lambda_i$ :

```
\lambda_{1}_true = 1.23

1 \lambda_{1}_true = 1.23

\lambda_{2}_true = 1.05

1 \lambda_{2}_true = 1.05

\lambda_{3}_true = 0.85

1 \lambda_{3}_true = 0.85
```

Now use  $\lambda_i$  to define **U**, the right stretch tensor:

Now let's create an arbitrary rotation tensor  $\mathbf{Q}$ , here a triplet of Euler angles, each  $\frac{\pi}{4}$  in radians, is used:

Finally this lets us define  $\mathbf{F}$ :

```
F = 3×3 Matrix{Float64}:
    0.615    -0.525     0.601041
    1.04987     0.153769    -0.425
    0.180129     0.896231     0.425

1 # Create simulated deformation gradient tensor F

2 F = 0_true*U_true
```

Next our job is to retrieve  $\mathbf{U}$ ,  $\mathbf{V}$ ,  $\mathbf{C}$ ,  $\lambda_i$  (and various strain metrics) from  $\mathbf{F}$ .

#### Using the singular value decomposition

One approach is to use the sinular value decomposition of  $\mathbf{F}$ , i.e.:

```
\mathbf{F} = \mathbf{W} \mathbf{\Sigma} \mathbf{R}
```

In Julia this can be achieved using LinearAlgebra's svd function.

```
1 Enter cell code...
```

```
SVD{Float64, Float64, Matrix{Float64}, Vector{Float64}}
U factor:
3×3 Matrix{Float64}:
                          0.707107
 -0.5
              0.5
 -0.853553
            -0.146447
                         -0.5
 -0.146447
            -0.853553
singular values:
3-element Vector{Float64}:
 1.23000000000000002
 1.05
 0.849999999999999
Vt factor:
3×3 Matrix{Float64}:
 -1.0 -0.0 -0.0
 -0.0 -1.0 -0.0
       0.0
  0.0
              1.0
 1 W, \Sigma, R = svd(\underline{F})
Q_svd = 3×3 Matrix{Float64}:
                    -0.5
         0.5
                                  0.707107
                     0.146447
         0.853553
                                 -0.5
         0.146447
                     0.853553
                                  0.5
 1 Q_svd = \underline{W} \times \underline{R}
U_svd = 3×3 Matrix{Float64}:
                      0.525
                                  -0.601041
         -0.615
         -1.04987
                     -0.153769
                                   0.425
          0.180129
                      0.896231
                                   0.425
 1 \quad U_svd = R'*F
V_svd = 3×3 Matrix{Float64}:
                      0.525
                                   0.601041
         -0.615
                     -0.153769
         -1.04987
                                 -0.425
         -0.180129 -0.896231
                                   0.425
 1 V_svd = F*R'
\lambda_{principal_svd} = [1.23, 1.05, 0.85]
 1 \lambda_{principal_svd} = \Sigma
n_1 = [-1.0, 0.0, 0.0]
 1 n_1 = R*[1.0,0.0,0.0]
n_2 = [0.0, -1.0, 0.0]
 1 n_2 = R*[0.0,1.0,0.0]
n_3 = [0.0, 0.0, 1.0]
 1 n_3 = R*[0.0,0.0,1.0]
```

## Using the eigen decomposition of the right Cauchy-Green tensor

Alternatively the eigen decomposition can be used. First we obtain a symmetric tensor by computing the right Cauchy-Green tensor  $\mathbf{C}$  from:  $\mathbf{C} = \mathbf{F}^{\top}\mathbf{F}$ 

The eigen values of  ${f C}$  are the squared principle stretches  ${\lambda_i}^2$ 

```
1 md"""
2 The eigen values of $\mathbf{C}$ are the squared principle stretches ${\lambda_i}^2$
3 """
```

```
Eigen{Float64, Float64, Matrix{Float64}, Vector{Float64}}
values:
3-element Vector{Float64}:
0.722499999999999
1.102499999999998
1.5129000000000001
vectors:
3×3 Matrix{Float64}:
0.0 -2.22045e-16 -1.0
0.0 -1.0 6.66134e-16
1.0 0.0 0.0

1 λ_sq, Q_eig = eigen(C)
```

To obtain the principal stretches  $\lambda_i$  we simply take the square root of the eigen values of **C** 

```
\lambda_{\text{principal}} = [0.85, 1.05, 1.23]
1 \lambda_{\text{principal}} = .\sqrt{\lambda_{\text{sq}}}
```

Next we can form the right stretch tensor  $\mathbf{U}$  in the principal component coordinate system by forming a diagonal matrix using the principal stretches.

And the same can be done with the squared principal stretches to get  ${\bf C}$  in the principal component system.

Next we can rotate the right stretch tensor in the principal component system to our regular system using the rotation tensor  $\mathbf{Q}$ 

```
1 md"""
2 Next we can rotate the right stretch tensor in the principal component system to
  our regular system using the rotation tensor $\mathbf{Q}$$
3 """
```

And similarly for the right Cauchy green tensor.

#### **Deriving strain metrics**

The natural or logarithmic strain:

$$\mathbf{E}_{log} = log(\mathbf{U})$$

The Green-Lagrange strain:

$$\mathbf{E}_{GL} = rac{1}{2}(\mathbf{U}^2 - \mathbf{I})$$

The Hencky ("linear") strain:

$$\mathbf{E}_H = \mathbf{U} - \mathbf{I}$$

```
E_lin = 3×3 Matrix{Float64}:
                       -1.42109e-16 -0.0
         -1.42109e-16
                        0.05
                                        0.0
         -0.0
                         0.0
                                       -0.15
 1 E_lin = 0_{eig}*Diagonal(\lambda_{principal} .- 1.0)*0_{eig}
```

Some other Seth-Hill strain:

$$\mathbf{E}_{SH} = rac{1}{m}(\mathbf{U}^m - \mathbf{I})$$

```
3×3 Matrix{Float64}:
                 -1.79484e-16 -0.0
  0.286956
                   0.0525417
 -1.79484e-16
                                      0.0
                                      -0.128625
 1 m=3.0; E_SH = \underline{0}_eig*Diagonal(1.0/\underline{m} .* (\underline{\lambda}_principal.^\underline{m} .- 1.0))*\underline{0}_eig'
 1 Enter cell code...
```