

Plots of input features

Features were proposed by Wang et al. (Wang, Wu, & Xiao, 2017)

The features are normalized according to:

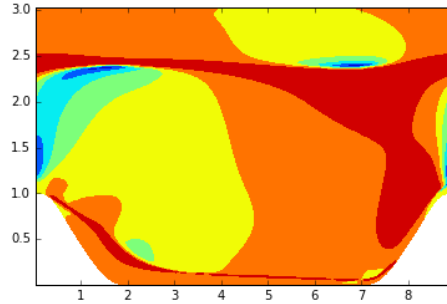
$$q_{\beta} = \frac{\hat{q}_{\beta}}{|\hat{q}_{\beta}| + |q_{\beta}^*|} \quad (1)$$

RANS data from openFOAM simulation (Re=700 and kOmega) with end-time 3000.

1. Ratio of excess rotation rate to strain rate

$$\hat{q}_{\beta} = \frac{1}{2}(\|\Omega\|^2 + \|S\|^2)$$
$$q_{\beta}^* = \|S\|^2$$

```
1 def q1(S, Omega):
2     a = np.shape(S)
3     q1 = np.zeros((a[2], a[3]))
4     for i1 in range(a[2]):
5         for i2 in range(a[3]):
6             raw = 0.5*(np.abs(np.trace(np.dot(S[:, :,
7             i1, i2], S[:, :, i1, i2]))) - np.abs(np.trace(np.dot(
8             Omega[:, :, i1, i2], -1*(Omega[:, :, i1, i2])))))
9             norm = np.trace(np.dot(S[:, :, i1, i2], S
10            [:, :, i1, i2]))
11             q1[i1, i2] = raw/(np.abs(raw) + np.abs(
12             norm))
13     return q1
```



2. Turbulence intensity

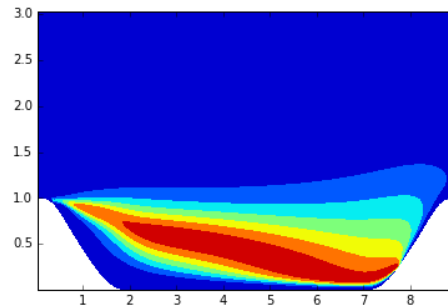
$$\hat{q}_\beta = k$$

$$q_\beta^* = \frac{1}{2} U_i U_i$$

```

1 def q2(k, U):
2     a = np.shape(k)
3     b = np.shape(U)
4     q2 = np.zeros((a[1], a[2]))
5     for i1 in range(a[1]):
6         for i2 in range(a[2]):
7             raw = k[0, i1, i2]
8             norm = 0.5*(np.inner(U[:, i1, i2], U[:,
9             i1, i2])) # inner is equivalent to sum UiUi
10            q2[i1, i2] = raw/(np.abs(raw) + np.abs(
11            norm))
12    return q2

```



3. Wall-distance based on Reynolds number

$$q_\beta = \min\left(\frac{\sqrt{k}d}{50\nu}, 2\right)$$

Normalization is not necessary since this feature is already non dimensional.

```

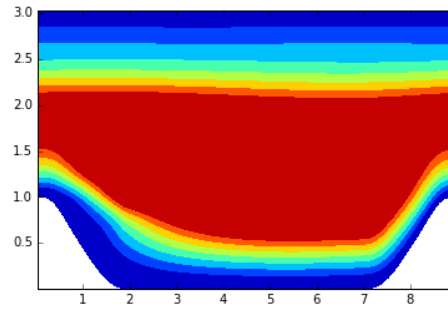
1 nu=1.4285714285714286e-03
2
3 def q3(k, yWall, nu):
4     a = np.shape(k)

```

```

5     q3 = np.zeros((a[1],a[2]))
6     for i1 in range(a[1]):
7         for i2 in range(a[2]):
8             q3[i1,i2] = np.minimum((np.sqrt(k[:,i1,i2]
9 ][0])*yWall[:, i1, i2])/(50*nu), 2)
10    return q3

```



4. Pressure gradient along streamline

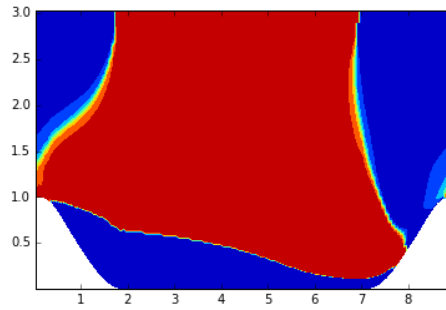
$$\hat{q}_\beta = U_i \frac{\partial P}{\partial x_i}$$

$$q_\beta^* = \sqrt{\frac{\partial P}{\partial x_j} \frac{\partial P}{\partial x_j} U_i U_i}$$

```

1 def q4(U, gradP):
2     a = np.shape(gradP)
3     q4 = np.zeros((a[1],a[2]))
4     for i1 in range(a[1]):
5         for i2 in range(a[2]):
6             raw = np.einsum('k,k', U[:,i1,i2], gradP
7 [:,i1,i2])
8             norm = np.einsum('j,j,i,i', gradP[:,i1,i2]
9 [:,i1,i2], gradP[:,i1,i2], U[:,i1,i2], U[:,i1,i2])
10            q4[i1,i2] = raw / (np.fabs(norm) + np.
11 fabs(raw));
12    return q4

```



5. Ratio of turbulent time scale to mean strain time scale

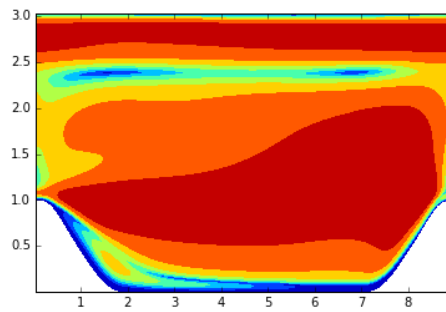
$$\hat{q}_\beta = \frac{k}{\epsilon}$$

$$q_\beta^* = \frac{1}{||S||}$$

```

1 Cmu=0.09
2 def q5(k, S, Cmu, omega):
3     a = np.shape(k_RANS)
4     q5 = np.zeros((a[1], a[2]))
5     for i1 in range(a[1]):
6         for i2 in range(a[2]):
7             epsilon = Cmu * k[:, i1, i2] * omega[:,
8             i1, i2]
9             raw = k[:, i1, i2] / epsilon
10            norm = 1 / np.sqrt(np.trace(np.dot(S[:,
11            :, i1, i2], S[:, :, i1, i2])))
12            q5[i1, i2] = raw / (np.fabs(raw) + np.fabs(
13            norm))
14    return q5

```



6. Cratio of pressure normal stresses to shear stresses

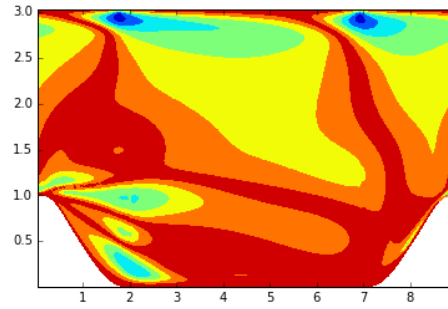
$$\hat{q}_\beta = \sqrt{\frac{\partial p}{x_i} \frac{\partial p}{\partial x_i}}$$

$$q_\beta^* = \frac{1}{2} \rho \left(\frac{\partial U_k}{\partial x_k} \right)^2$$

```

1 def q6(gradP, gradU, p, U):
2     a = np.shape(gradP)
3     q6 = np.zeros((a[1], a[2]))
4     for i1 in range(a[1]):
5         for i2 in range(a[2]):
6             raw = np.sqrt(np.einsum('i,i', gradP[:,
7             i1, i2], gradP[:, i1, i2]))
8             norm = np.einsum('k,kk', U[:, i1, i2],
9             gradU[:, :, i1, i2])
10            norm *= 0.5 * p[0, i1, i2]
11            q6[i1, i2] = raw / (np.fabs(raw) + np.fabs(
12            norm))
13    return q6

```



7. Non-orthogonality between velocity and its gradient

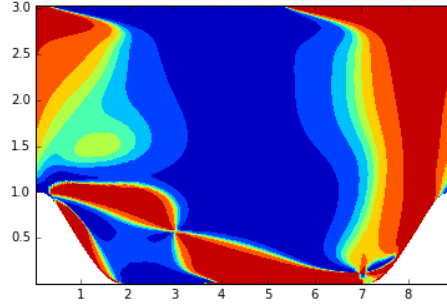
$$\hat{q}_\beta = |U_i U_j \frac{\partial U_i}{\partial x_j}|$$

$$q_\beta^* = \sqrt{U_l U_l U_i \frac{\partial U_i}{\partial x_j} U_k \frac{\partial U_k}{\partial x_j}}$$

```

1 def q7(U, gradU):
2     a = np.shape(U)
3     q7 = np.zeros((a[1], a[2]))
4     for i1 in range(a[1]):
5         for i2 in range(a[2]):
6             raw = np.fabs(np.einsum('i, j, ij', U[:,
7             i1, i2], U[:, i1, i2], gradU[:, :, i1, i2]))
8             norm = np.sqrt(np.einsum('l, l, i, ij, k,
9             kj', U[:, i1, i2], U[:, i1, i2], U[:, i1, i2],
10            gradU[:, :, i1, i2], U[:, i1, i2], gradU[:, :, i1,
11            i2]))
12            q7[i1, i2] = raw/(np.fabs(raw) + np.fabs(
13            norm))
14    return q7

```



8. Ratio of convection to production of TKE

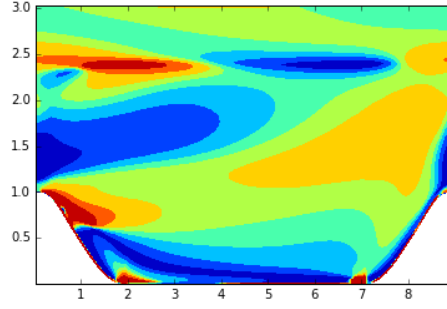
$$\hat{q}_\beta = U_i \frac{dk}{dx_i}$$

$$q_\beta^* = |\overline{u'_i u'_j} S_{jk}|$$

```

1 def q8(U, gradK, Tau, S):
2     a = np.shape(U)
3     q8 = np.zeros((a[1], a[2]))
4     for i1 in range(a[1]):
5         for i2 in range(a[2]):
6             raw = np.einsum('i, i', U[:, i1, i2], gradK
7            [:, i1, i2])
8             norm = np.einsum('jk, jk', Tau[:, :, i1, i2],
9             S[:, :, i1, i2])
10            q8[i1, i2] = raw/(np.fabs(raw) + np.fabs(
11            norm))
12    return q8

```



9. Ratio of total to normal Reynolds stresses

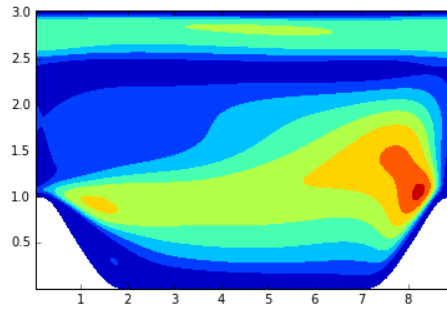
$$\hat{q}_\beta = \overline{||u'_i u'_j||}$$

$$q_\beta^* = k$$

```

1 def q9(tau, k):
2     a = np.shape(k)
3     q9 = np.zeros((a[1], a[2]))
4     for i1 in range(a[1]):
5         for i2 in range(a[2]):
6             raw = np.sqrt(np.trace(np.dot(tau[:, :,
7             i1, i2], np.transpose(tau[:, :, i1, i2]))))
8             norm = k[:, i1, i2]
9             q9[i1, i2] = raw/(np.fabs(raw) + np.fabs(
norm))
10    return q9

```



References

Wang, J.-X., Wu, J.-L., & Xiao, H. (2017). Physics-informed machine learning approach for reconstructing reynolds stress modeling discrepancies based on dns data. *Physical Review Fluids*, 2(3), 034603.