Solution to Ex. 13.21

of Turbulent Flows by Stephen B. Pope, 2000

Yaoyu Hu April 13, 2017

For a general filter $G(\mathbf{r}, \mathbf{x})$ satisfying the normalization condition Eq. (13.2), the filtered density function (Pope 1990) is defined by

$$\overline{f}(\mathbf{V}; \mathbf{x}, t) = \int G(\mathbf{r}, \mathbf{x}) \delta \left[\mathbf{U}(\mathbf{x} - \mathbf{r}, t) - \mathbf{V} \right] d\mathbf{r}$$
(1)

Obtain the results

$$\overline{\mathbf{U}} = \int \mathbf{V} \overline{f} \left(\mathbf{V}; \mathbf{x}, t \right) d\mathbf{V} \tag{2}$$

$$\overline{U_i U_j} = \int V_i V_j \overline{f} \left(\mathbf{V}; \mathbf{x}, t \right) d\mathbf{V}$$
 (3)

$$\tau_{ij}^{R} = \int (V_i - \overline{U}_i)(V_j - \overline{U}_j)\overline{f}(\mathbf{V}; \mathbf{x}, t)d\mathbf{V}$$
(4)

where integration is over all \mathbf{V} ; and $\overline{\mathbf{U}}$, $\overline{U_i U_j}$, and τ_{ij}^R are evaluated at \mathbf{x} , t. Show that \overline{f} satisfies the normalization condition Eq. (12.1) and that, if the filter is everywhere non-negative, then \overline{f} is also non-negative, and hence has the properties of a joint PDF. Argue that, for such positive filters, the residual stress τ_{ij}^R is positive semi-definite (Gao and O'Brien 1993). Use similar reasoning to show that L_{ij}^o and R_{ii}^o (Eqs. (13.100) and (13.102)) are also positive semi-definite for positive filters.

Solution

$$\int \overline{f}(\mathbf{V}; \mathbf{x}, t) d\mathbf{V} = \iint G(\mathbf{r}, \mathbf{x}) \delta \left[\mathbf{U}(\mathbf{x} - \mathbf{r}, t) - \mathbf{V} \right] d\mathbf{r} d\mathbf{V}$$

$$= \iint G(\mathbf{r}, \mathbf{x}) \int \delta \left[\mathbf{U}(\mathbf{x} - \mathbf{r}, t) - \mathbf{V} \right] d\mathbf{V} d\mathbf{r}$$

$$= \iint G(\mathbf{r}, \mathbf{x}) d\mathbf{r}$$

$$= 1$$
(5)

This means the filtered density function satisfies the normalization condition. If G(r, x) is non-negative, from Eq. (1) it is clear that \overline{f} is also non-negative.

$$\int \mathbf{V} \overline{f} (\mathbf{V}; \mathbf{x}, t) d\mathbf{V} = \int \mathbf{V} \int G(\mathbf{r}, \mathbf{x}) \delta \left[\mathbf{U} (\mathbf{x} - \mathbf{r}, t) - \mathbf{V} \right] d\mathbf{r} d\mathbf{V}$$

$$= \int G(\mathbf{r}, \mathbf{x}) \int \mathbf{V} \delta \left[\mathbf{U} (\mathbf{x} - \mathbf{r}, t) - \mathbf{V} \right] d\mathbf{V} d\mathbf{r}$$

$$= \int G(\mathbf{r}, \mathbf{x}) \mathbf{U} (\mathbf{x} - \mathbf{r}, t) d\mathbf{r}$$

$$= \overline{\mathbf{U}} (\mathbf{x}, t)$$
(6)

$$\int V_{i}V_{j}\overline{f}(\mathbf{V};\mathbf{x},t)d\mathbf{V} = \int V_{i}V_{j}\int G(\mathbf{r},\mathbf{x})\delta \left[\mathbf{U}(\mathbf{x}-\mathbf{r},t)-\mathbf{V}\right]d\mathbf{r}d\mathbf{V}$$

$$= \int G(\mathbf{r},\mathbf{x})\int V_{i}V_{j}\delta \left[\mathbf{U}(\mathbf{x}-\mathbf{r},t)-\mathbf{V}\right]d\mathbf{V}d\mathbf{r}$$

$$= \int G(\mathbf{r},\mathbf{x})U_{i}(\mathbf{x}-\mathbf{r},t)U_{j}(\mathbf{x}-\mathbf{r},t)d\mathbf{r}$$

$$= \overline{U_{i}(\mathbf{x},t)U_{j}(\mathbf{x},t)}$$
(7)

$$\int (V_{i} - \overline{U}_{i})(V_{j} - \overline{U}_{j}) \overline{f}(\mathbf{V}; \mathbf{x}, t) d\mathbf{V}$$

$$= \int (V_{i}V_{j} - V_{i}\overline{U}_{j} - \overline{U}_{i}V_{j} + \overline{U}_{i}\overline{U}_{j}) \overline{f}(\mathbf{V}; \mathbf{x}, t) d\mathbf{V}$$

$$= \int V_{i}V_{j} \overline{f}(\mathbf{V}; \mathbf{x}, t) d\mathbf{V} - \overline{U}_{j} \int V_{i} \overline{f}(\mathbf{V}; \mathbf{x}, t) d\mathbf{V} - \overline{U}_{i} \int V_{j} \overline{f}(\mathbf{V}; \mathbf{x}, t) d\mathbf{V} + \overline{U}_{i}\overline{U}_{j} \int \overline{f}(\mathbf{V}; \mathbf{x}, t) d\mathbf{V}$$

$$= \overline{U_{i}U_{j}} - \overline{U}_{j}\overline{U}_{i} - \overline{U}_{i}\overline{U}_{j} + \overline{U}_{i}\overline{U}_{j}$$

$$= \overline{U_{i}U_{j}} - \overline{U}_{i}\overline{U}_{j}$$

$$= \overline{U_{i}U_{j}} - \overline{U}_{i}\overline{U}_{j}$$

$$= \overline{U_{i}U_{j}} - \overline{U}_{i}\overline{U}_{j}$$

$$= \overline{U_{i}U_{j}} - \overline{U}_{i}\overline{U}_{j}$$

From the above equations we can write

$$\tau_{ij}^{R} = \overline{U_{i}U_{j}} - \overline{U}_{i}\overline{U}_{j}$$

$$= \int V_{i}V_{j}\overline{f}(\mathbf{V};\mathbf{x},t)d\mathbf{V} - \int V_{i}\overline{f}(\mathbf{V};\mathbf{x},t)d\mathbf{V} \int V_{j}\overline{f}(\mathbf{V};\mathbf{x},t)d\mathbf{V}$$
(9)

For arbitrary vector **Y**, and let $A(\mathbf{V}) = Y_i V_i$.

$$\tau_{ij}^{R}Y_{i}Y_{j} = Y_{i}Y_{j}\left(\overline{U_{i}U_{j}} - \overline{U_{i}}\overline{U_{j}}\right)$$

$$= Y_{i}Y_{j}\int V_{i}V_{j}\overline{f}\left(\mathbf{V};\mathbf{x},t\right)d\mathbf{V} - Y_{i}Y_{j}\int V_{i}\overline{f}\left(\mathbf{V};\mathbf{x},t\right)d\mathbf{V}\int V_{j}\overline{f}\left(\mathbf{V};\mathbf{x},t\right)d\mathbf{V}$$

$$= \int Y_{i}V_{i}Y_{j}V_{j}\overline{f}\left(\mathbf{V};\mathbf{x},t\right)d\mathbf{V} - \int Y_{i}V_{i}\overline{f}\left(\mathbf{V};\mathbf{x},t\right)d\mathbf{V}\int Y_{j}V_{j}\overline{f}\left(\mathbf{V};\mathbf{x},t\right)d\mathbf{V}$$

$$= \int A^{2}\left(\mathbf{V}\right)\overline{f}\left(\mathbf{V};\mathbf{x},t\right)d\mathbf{V} - \int A\left(\mathbf{V}\right)\overline{f}\left(\mathbf{V};\mathbf{x},t\right)d\mathbf{V}\int A\left(\mathbf{V}\right)\overline{f}\left(\mathbf{V};\mathbf{x},t\right)d\mathbf{V}$$

$$= \int \overline{f}\left(\mathbf{V};\mathbf{x},t\right)d\mathbf{V}\int A^{2}\left(\mathbf{V}\right)\overline{f}\left(\mathbf{V};\mathbf{x},t\right)d\mathbf{V} - \int A\left(\mathbf{V}\right)\overline{f}\left(\mathbf{V};\mathbf{x},t\right)d\mathbf{V}\int A\left(\mathbf{V}\right)\overline{f}\left(\mathbf{V};\mathbf{x},t\right)d\mathbf{V}$$

$$\stackrel{*}{\geq}\left(\int A\left(\mathbf{V}\right)\overline{f}\left(\mathbf{V};\mathbf{x},t\right)d\mathbf{V}\right)^{2} - \int A\left(\mathbf{V}\right)\overline{f}\left(\mathbf{V};\mathbf{x},t\right)d\mathbf{V}\int A\left(\mathbf{V}\right)\overline{f}\left(\mathbf{V};\mathbf{x},t\right)d\mathbf{V}$$

$$= 0$$

where the inequality marked by * is the direct result of the Cauchy-Schwarz inequality and the fact that \overline{f} is positive

$$\int \overline{f}(\mathbf{V}; \mathbf{x}, t) d\mathbf{V} \int A^{2}(\mathbf{V}) \overline{f}(\mathbf{V}; \mathbf{x}, t) d\mathbf{V}$$

$$= \int \left[\sqrt{\overline{f}(\mathbf{V}; \mathbf{x}, t)} \right]^{2} d\mathbf{V} \int \left[A(\mathbf{V}) \sqrt{\overline{f}(\mathbf{V}; \mathbf{x}, t)} \right]^{2} d\mathbf{V}$$

$$\geq \left[\int \sqrt{\overline{f}(\mathbf{V}; \mathbf{x}, t)} A(\mathbf{V}) \sqrt{\overline{f}(\mathbf{V}; \mathbf{x}, t)} d\mathbf{V} \right]^{2}$$

$$= \int A(\mathbf{V}) \overline{f}(\mathbf{V}; \mathbf{x}, t) d\mathbf{V} \int A(\mathbf{V}) \overline{f}(\mathbf{V}; \mathbf{x}, t) d\mathbf{V}$$
(11)

This derivation is inspired by my colleague DONG Bing <dongbing@sjtu.edu.cn>.

As for Leonard stresses L_{ij}^o we can define a new filtered density function

$$\overline{f^{L}}(\mathbf{V};\mathbf{x},t) = \int G(\mathbf{r},\mathbf{x}) \delta \overline{\mathbf{U}}(\mathbf{x}-\mathbf{r},t) - \mathbf{V} d\mathbf{r}$$
(12)

Then

$$\int \mathbf{V} \overline{f^{L}} (\mathbf{V}; \mathbf{x}, t) d\mathbf{V} = \int \mathbf{V} \int G(\mathbf{r}, \mathbf{x}) \delta \left[\overline{\mathbf{U}} (\mathbf{x} - \mathbf{r}, t) - \mathbf{V} \right] d\mathbf{r} d\mathbf{V}$$

$$= \int G(\mathbf{r}, \mathbf{x}) \int \mathbf{V} \delta \left[\overline{\mathbf{U}} (\mathbf{x} - \mathbf{r}, t) - \mathbf{V} \right] d\mathbf{V} d\mathbf{r}$$

$$= \int G(\mathbf{r}, \mathbf{x}) \overline{\mathbf{U}} (\mathbf{x} - \mathbf{r}, t) d\mathbf{r}$$

$$= \overline{\overline{\mathbf{U}}} (\mathbf{x}, t)$$
(13)

Here we have two pairs of analogies with \overline{f}^L to \overline{f} and $\overline{\overline{\mathbf{U}}}$ to $\overline{\mathbf{U}}$. If we take \mathbf{U} to be a general random process \mathbf{B} , then Eq. (10) tells us that a tensor defined by $\overline{B_iB_j} - \overline{B_i}\overline{B}_j = \overline{U_iU_j} - \overline{U}_i\overline{U}_j$ is positive semi-definite. Since L_{ij}^o is defined to be

$$L_{ii}^{o} = \overline{\overline{U}_{i}}\overline{\overline{U}_{j}} - \overline{\overline{U}_{i}}\overline{\overline{U}_{j}}$$

$$\tag{14}$$

And if we take $\overline{\mathbf{U}}$ to be the general random process \mathbf{B} , then L_{ij}^o must be semi-definite due to the same reason expressed by Eq. (10).

_

¹ https://en.wikipedia.org/wiki/Cauchy%E2%80%93Schwarz_inequality

Because the SGS Reynolds stresses are defined in the same way of L^o_{ij}

$$R_{ij}^{o} = \overline{u_i' u_j'} - \overline{u_i'} \overline{u_j'}$$
 (15)

And we take \mathbf{u}' as the general random process \mathbf{B} , then R_{ij}^o is also semi-definite.