

Combining Several Estimates

j.p.lewis

October 17, 2001

Maybeck's Kalman tutorial gives a formula for combining several estimates but does not derive it. Likewise I don't see this explicitly in Papoulis, though the ingredients are all there.

Given two estimates x_1, x_2 of the same quantity x , but assuming that the two estimates are not necessarily equally reliable, and thus assigning differing σ_1, σ_2 , how to combine them to form a single estimate?

This can be done by applying the orthogonality principle, and by requiring that the resulting estimate be unbiased. The estimate will be a linear combination of the two observations:

$$\hat{x} = w_1 x_1 + w_2 x_2$$

Starting with the no-bias requirement,

$$E[x - \hat{x}] = 0$$

Rewrite the observations x_1, x_2 as the true value x plus observation noise r_1, r_2 .

$$\begin{aligned} x_1 &= x + r_1, & x_2 &= x + r_2 \\ E[x - (w_1(x + r_1) + w_2(x + r_2))] &= 0 \\ x &= w_1(x + E(r_1)) + w_2(x + E(r_2)) \\ &\quad \text{but if } E(r_1) = E(r_2) = 0 \\ x &= w_1 x + w_2 x \\ w_1 + w_2 &= 1 \end{aligned}$$

so the weights must sum to one if the observations and the resulting estimate are unbiased. Hmm...

Next apply the orthogonality principle:

$$\begin{aligned} E[(w_1 x_1 + w_2 x_2 - x)x_1] &= 0 \quad \text{"e1"} \\ E[(w_1 x_1 + w_2 x_2 - x)x_2] &= 0 \quad \text{"e2"} \end{aligned}$$

expand e1:

$$E[w_1(x + r_1)(x + r_1) + w_2(x + r_2)(x + r_1) - x(x + r_1)] = 0$$

in

$$(x + r_1)(x + r_1) = x^2 + xr_1 + xr_2 + r_1^2$$

we assume that r_1, r_2 are uncorrelated

and uncorrelated with x , so

e1 after expanding and cancelling uncorrelated terms:

$$E[w_1(x^2 + r_1^2) + w_2x^2 - x] = 0$$

do the same with e2:

$$E[w_1x^2 + w_2(x^2 + r_2^2) - x] = 0$$

and subtract this from the similarly processed e1

$$E[w_1(x^2 + r_1^2 - x^2) + w_2(x^2 - x^2 - r_2^2)] = 0$$

$$w_1E[r_1^2] = w_2E[r_2^2]$$

$$\frac{w_1}{w_2} = \frac{\sigma_2^2}{\sigma_1^2}$$

Now substitute $w_2 = 1 - w_1$ because the weights sum to 1,

$$\frac{w_1}{1 - w_1} = \frac{\sigma_2^2}{\sigma_1^2}$$

$$w_1 = (1 - w_1) \frac{\sigma_2^2}{\sigma_1^2}$$

$$= \frac{\sigma_2^2}{\sigma_1^2} - w_1 \frac{\sigma_2^2}{\sigma_1^2}$$

$$w_1 \left(1 + \frac{\sigma_2^2}{\sigma_1^2}\right) = \frac{\sigma_2^2}{\sigma_1^2}$$

$$w_1 = \frac{\sigma_2^2}{\sigma_1^2 \left(1 + \frac{\sigma_2^2}{\sigma_1^2}\right)}$$

$$= \frac{\sigma_2^2}{\sigma_1^2 + \sigma_2^2}$$

This is similar to the formula in Maybeck.