

linear predictor $\hat{v}(t_i) = \hat{v}_n + \hat{a}_n(t_i - t_n)$

\hat{a}_n and \hat{v}_n are estimated from buffered data sample (past measures over $N^\bullet - 1$ cycles + current sample) according to the least squares fitting method (i.e. by minimizing the sum of squared residuals)

$$Q(\hat{v}_n, \hat{a}_n) = \sum_i e_i^2 = \sum_{i=n}^{n-N^\bullet+1} [v_i - \hat{v}(t_i)]^2 = \sum_{i=n}^{n-N^\bullet+1} [v_i - \hat{v}_n - \hat{a}_n(t_i - t_n)]^2$$

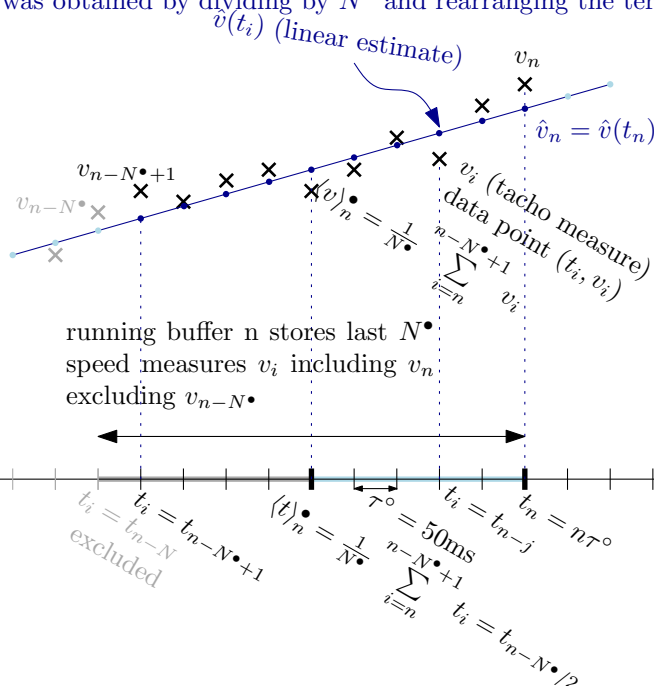
by setting the derivative to zero we obtain

$$\frac{\partial Q(\hat{v}_n, \hat{a}_n)}{\partial \hat{a}_n} = \sum_{i=n}^{n-N^\bullet+1} -2[v_i - \hat{v}_n - \hat{a}_n(t_i - t_n)](t_i - t_n) = 0$$

$$\sum_{i=n}^{n-N^\bullet+1} (v_i - \hat{v}_n)(t_i - t_n) = \hat{a}_n \sum_{i=n}^{n-N^\bullet+1} (t_i - t_n)^2$$

$$\hat{a}_n = \frac{\frac{1}{N^\bullet} \sum_{i=n}^{n-N^\bullet+1} (v_i - \hat{v}_n)(t_i - t_n)}{\frac{1}{N^\bullet} \sum_{i=n}^{n-N^\bullet+1} (t_i - t_n)^2}$$

last step was obtained by dividing by N^\bullet and rearranging the terms:



canonical form with intercept at data center

$$\hat{v}(t_i) = \langle v \rangle_n^\bullet + \hat{a}_n (t_i - \langle t \rangle_n^\bullet)$$

$$\hat{v}(t_{n-j}) = \hat{v}_n + \hat{a}_n(-j\tau^\circ)$$

delay index $j : t_i = t_{n-j} = t_n - j\tau^\circ$

