Supporting Information to

Estimation of Migration-time and Mobility Distributions in Organelle Capillary Electrophoresis with Statistical-Overlap Theory

by

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This Supporting Information contains five parts. Each part identifies the relevant section of the main article. The terminology is the same as the main article.

## Part 1. Conversion between $\alpha$ and $\alpha_e$

The conversions between saturation  $\alpha$  and effective saturation  $\alpha_e$  are mentioned in the paragraph of the main article after eq 2b. They are appropriate for an exponential distribution of peak heights. Over the range,  $0 \le \alpha_e \le 25$ ,  $\alpha_e$  can be converted to  $\alpha$ using the empirical expression<sup>1</sup>

$$\alpha = \frac{0.725\alpha_e}{1 + \delta_1 \alpha_e^{\delta_2}} \tag{S-1}$$

with  $\delta_1 = 0.1942 \pm 0.0005$  and  $\delta_2 = 0.930 \pm 0.001$ . Over the range,  $0 \le \alpha \le 3.85$ ,  $\alpha$  is converted to  $\alpha_e$  on dividing  $\alpha$  by  $R_s^*$ , as expressed by eq 4c in the main article.

## Part 2. Standard deviation $\sigma_{m_e}$ of $m_e$ distribution

The standard deviation  $\sigma_{m_e}$  is first mentioned in the paragraph of the main article containing eq 4.

Theory. Consider a separation ensemble containing peaks of constant density and width, with peak numbers and migration times obeying Poisson statistics. Each member of the ensemble contains m peaks and p observed peaks. Consider equating p to

$$\overline{p} = \overline{m} \exp(-\alpha) \tag{S-2}$$

where

$$\alpha = 4\overline{m}\,\sigma R_s^* \,/\, X \tag{S-3}$$

and solving for  $\overline{m}$ . (Eqs S-2 and S-3 are eqs 1b and 1a, respectively, in the main article.) Here,  $\overline{m}$  and  $\overline{p}$  are the mean numbers of peaks and observed peaks in the ensemble,  $\alpha$  is the saturation,  $\sigma$  is the peak standard deviation,  $R_s^*$  is the average minimum resolution (which depends on  $\alpha$ ), and X is the duration of the separation. We assume  $\overline{m}$  is the only unknown, with  $\sigma$ , X, and  $R_s^*$  being known or calculable. The determined  $\overline{m}$  is interpreted as the estimated number of peaks,  $m_e$ .

We assume that  $m_e$  is distributed randomly about  $\overline{m}$ , just as p is distributed randomly about  $\overline{p}$ . The difference  $\Delta m = m_e - \overline{m}$  is related to the difference  $\Delta p = p - \overline{p}$ by the first-order Taylor series

$$\Delta m \approx \frac{\partial \overline{m}}{\partial \overline{p}} \Delta p = \frac{\partial \overline{m}}{\partial \alpha} \frac{\partial \alpha}{\partial \overline{p}} \Delta p \tag{S-4}$$

where the final identity results from the chain rule (the derivatives are partials because  $\sigma/X$  is constant). The theory of the propagation of errors<sup>2</sup> is applied to *J* independent members of the ensemble by adding the squares of the left- and right-hand sides of eq S-4 and dividing by *J* 

$$J^{-1}\sum_{i=1}^{J} (m_{ei} - \overline{m})^2 \approx J^{-1} \left[ \frac{\partial \overline{m}}{\partial \alpha} \frac{\partial \alpha}{\partial \overline{p}} \right]^2 \sum_{i=1}^{J} (p_i - \overline{p})^2$$
(S-5)

where  $p_i$  and  $m_{ej}$  are the p and  $m_e$  values of the *i*<sup>th</sup> ensemble member. The derivatives are factored out of the sum in eq S-5, because they are the same for every ensemble member. As J approaches infinity, eq S-5 has the limit

$$\sigma_{m_e}^2 = \left[\frac{\partial \overline{m}}{\partial \alpha} \frac{\partial \alpha}{\partial \overline{p}}\right]^2 \sigma_p^2 \tag{S-6}$$

where  $\sigma_{m_e}^2$  and  $\sigma_p^2$  are the variances of  $m_e$  and p, respectively. For peaks that are Poisson distributed,  $\sigma_p^2$  is

$$\sigma_p^2 = \overline{m} \exp(-\alpha)[1 - 2\alpha \exp(-\alpha)]$$
 (S-7)

(Eq S-7 is eq 3 in the main article.)

The derivatives in eq S-6 are evaluated simply. In accordance with eqs S-2 and S-3,  $\overline{m}$  and  $\overline{p}$  equal

$$\overline{m} = \alpha / (zR_s^*); \ \overline{p} = \alpha \exp(-\alpha) / (zR_s^*)$$
(S-8)

with  $z = 4\sigma / X$ . For constant peak widths (i.e., constant z)

$$\frac{\partial \overline{m}}{\partial \alpha} = \overline{m} \Big[ \alpha^{-1} - d \ln R_s^* / d\alpha \Big]$$
 (S-9)

and

$$\frac{\partial \overline{p}}{\partial \alpha} = \overline{m} \exp(-\alpha) \left( \alpha^{-1} - 1 - d \ln R_s^* / d\alpha \right)$$
(S-10)

where  $d \ln R_s^* / d\alpha$  is  $[dR_s^* / d\alpha] / R_s^*$ .

We want the reciprocal of eq S-10,  $\partial \alpha / \partial \overline{p}$ , which in combination with eqs S-6 and S-9 gives

$$\sigma_{m_e}^2 = [g(\alpha)]^2 \sigma_p^2 \tag{S-11a}$$

with

$$g(\alpha) = \frac{\alpha^{-1} - d\ln R_s^* / d\alpha}{\exp(-\alpha)[\alpha^{-1} - 1 - d\ln R_s^* / d\alpha]}$$
(S-11b)

where  $g(\alpha)$  is the reciprocal of the slope,  $\partial \overline{p} / \partial \overline{m}$ , of the  $\overline{p}$  vs  $\overline{m}$  curve. When combined with eq S-7, the square root of eq S-11a gives  $\sigma_{m_e}$  as a function of  $\overline{m}$  and  $\alpha$ 

$$\sigma_{m_e} = \left(\overline{m}[1 - 2\alpha \exp(-\alpha)]\right)^{1/2} \frac{\exp(\alpha/2)[\alpha^{-1} - d\ln R_s^*/d\alpha]}{\alpha^{-1} - 1 - d\ln R_s^*/d\alpha}$$
(S-12)

The coefficient of variation (*CV*),  $100\sigma_{m_e}/\overline{m}$ , can be calculated from eq S-12. On substituting the left-hand side of eq S-8 for  $\overline{m}$  in eq S-12 and the *CV*, we obtain

$$\sigma_{m_{e}}(\sigma/X)^{1/2} = \frac{1}{2} \left( \frac{\alpha}{R_{s}^{*}} [1 - 2\alpha \exp(-\alpha)] \right)^{1/2} \frac{\exp(\alpha/2)[\alpha^{-1} - d\ln R_{s}^{*}/d\alpha]}{\alpha^{-1} - 1 - d\ln R_{s}^{*}/d\alpha} \quad (S-13a)$$
$$\frac{CV}{(\sigma/X)^{1/2}} = 200 \left( \frac{R_{s}^{*}}{\alpha} [1 - 2\alpha \exp(-\alpha)] \right)^{1/2} \frac{\exp(\alpha/2)[\alpha^{-1} - d\ln R_{s}^{*}/d\alpha]}{\alpha^{-1} - 1 - d\ln R_{s}^{*}/d\alpha} \quad (S-13b)$$

which are eqs 4a and 4b in the main article. Both  $R_s^*$  and  $d \ln R_s^* / d\alpha$  can be evaluated from eq 4c in that article.

The denominator of the final factor in eq S-13 is the negative of the bracketed term in eq 5 of the main article. The latter is proportional to the slope,  $\partial \overline{p} / \partial \overline{m}$ . Thus,  $\sigma_{m_e}$  and the *CV* approach infinity as  $\partial \overline{p} / \partial \overline{m}$  approaches zero.

In accordance with Poisson statistics, the standard deviation  $\sigma_m$  of the number of peaks in the ensemble is  $\sqrt{m}$ . It differs from  $\sigma_{m_e}$ , which is the standard deviation of the *estimated* numbers of peaks  $m_e$ . The ratio  $\sigma_{m_e}/\sigma_m$  is calculated from eq S-12 as

$$\frac{\sigma_{m_e}}{\sigma_m} = \left(1 - 2\alpha \exp(-\alpha)\right)^{1/2} \frac{\exp(\alpha/2)[\alpha^{-1} - d\ln R_s^*/d\alpha]}{\alpha^{-1} - 1 - d\ln R_s^*/d\alpha}$$
(S-14)

and depends only on  $\alpha$ .

Results and discussion. Figure S-1a is a graph of the ratio  $\sigma_{m_e}/\sigma_m$  vs saturation  $\alpha$ , as calculated from eq S-14. As the saturation approaches zero, the ratio approaches one. This is expected, since at zero saturation all peaks are resolved and  $p = m = m_e$  for each ensemble member. As  $\alpha$  increases,  $\sigma_{m_e}/\sigma_m$  rapidly increases (e.g,  $\sigma_{m_e} = 3.40 \sigma_m$  at  $\alpha = 1$ ) and the precision of  $m_e$  decreases.

As discussed in the main article, the poor precision of  $m_e$  at high saturation results from the decreasing slope  $\partial \overline{p} / \partial \overline{m}$ , which maps small random fluctuations of p into large random fluctuations of  $m_e$ . Figure S-1b is a graph of  $g(\alpha)$  vs  $\alpha$ , where  $g(\alpha)$ , eq S-11b, is the reciprocal of this slope. It resembles Figure S-1a but increases with  $\alpha$  even more rapidly. Values of  $g(\alpha)$  agree with the reciprocal slope determined numerically from the graph of  $\overline{p}$  vs  $\overline{m}$ .

#### Part 3. Monte-Carlo simulation of *m<sub>e</sub>* distribution

The Monte-Carlo simulations are mentioned in the main article after eq 4c.

*Procedures.* To characterize the  $m_e$  distribution, 2 x 10<sup>5</sup> Monte-Carlo simulations of p and m, and calculations of  $m_e$ , were made. In each simulation, a Poisson distributed number m of Gaussian peaks having constant standard deviation  $\sigma$  and exponentially random heights spanned an interval of duration X, with peak overlap producing p observed peaks (maxima). This p then determined  $m_e$  via eqs S-2 and S-3 in Part 2 of the Supporting Information. Discrete distributions were built from the p, m, and  $m_e$  values. Further details are given in the Procedures section of the main article.

Results and Discussion. The panels in Figure S-2 are graphs of probability vs p, m, and  $m_e$  at different saturations  $\alpha$ , as determined for  $\sigma/X = 8 \ge 10^{-5}$ . All distributions are discrete but are shown as continuous functions for simplicity. At low saturation (e.g.,  $\alpha = 0.2$ ), the m and  $m_e$  distributions are almost identical. As  $\alpha$  increases, the  $m_e$ distribution becomes broader than the m distribution, and its average shifts slightly downward from the mean of the m distribution,  $\overline{m}$ . The shift occurs, because eq S-2 slightly underestimates peak overlap as  $\alpha$  increases. Values of  $\sigma_{m_e}$  calculated from eq S-12 in Part 2 of the Supporting Information and from moments analysis of the  $m_e$ distributions are reported in the panels. At low  $\alpha$ , excellent agreement is found. At higher  $\alpha$ , eq S-12 overpredicts the standard deviation of  $m_e$ . In all cases,  $\sigma_{m_e}$  exceeds the standard deviation of the m distribution, which is  $\sqrt{m}$  (and calculable from the  $\overline{m}$ 's reported in the panels). Further verification of eq S-12 is provided in the main article.

#### **Part 4.** Equations for migration-time distributions $f(\zeta)$

The equations are mentioned in the main article at the end of the first paragraph in the section, "Analysis of Migration-Time Distributions", under Procedures. All migration-time distributions  $f(\zeta)$  are models, have unit area, and are bound by the reduced times,  $\zeta = 0$  and  $\zeta = 1$ . Normalization coefficients were obtained by integrating  $f(\zeta)$  between these bounds. Various coefficients were selected by trial and error to obtain the desired

appearance of  $f(\zeta)$ . Equations are given for the reduced migration times  $\zeta_c$  of peaks. All random numbers *R* are uniform and bound by the integers, 0 and 1.

Gaussian  $f(\zeta)$ . The Gaussian migration-time distribution is

$$f(\zeta) = (2\pi\sigma_G^2)^{-1} \exp[-(\zeta - \mu)^2 / (2\sigma_G^2)]$$
 (S-15a)

with  $\mu = 0.5$  and  $\sigma_G = 0.125$ . A peak migration time  $\zeta_c$  was calculated with the Box-Muller transform<sup>3</sup>

$$\zeta_c = \mu + \sigma_G \left[ \sqrt{-2\ln R_1} \sin(2\pi R_2) \right]$$
(S-15b)

where  $R_1$  and  $R_2$  are independent random numbers (the radicand in eq S-15b is positive because  $\ln R_1$  is negative).

Strictly, eq S-15a is not normalized between  $\zeta = 0$  and  $\zeta = 1$ . However, the area between these bounds is  $\operatorname{erf}(4/\sqrt{2}) \approx 0.9999^+$ , where erf is the error function. The very small fraction (< 0.01%) of peak migration times generated by eq S-15b outside the bounds was not used; its discard had negligible effect on results.

*Bimodal*  $f(\zeta)$ . The bimodal migration-time distribution is

$$f(\zeta) = A_1 \left\{ \zeta \exp(-\kappa_1 \zeta) + (1 - \zeta) \exp(-\kappa_2 [1 - \zeta]^2) \right\}$$
(S-16a)

with  $\kappa_1$  and  $\kappa_2$  equaling constants (in the main article,  $\kappa_1 = 6.5$  and  $\kappa_2 = 8.5$ ). The normalization constant  $A_1$  is

$$A_{1} = \left\{ \left[ 1 - \exp(-\kappa_{2}) \right] / (2\kappa_{2}) - \exp(-\kappa_{1}) / \kappa_{1} + \left[ 1 - \exp(-\kappa_{1}) \right] / \kappa_{1}^{2} \right\}^{-1}$$
(S-16b)

A peak migration time  $\zeta_c$  was determined by solving

$$(\kappa_1)^{-2} - \exp(-\kappa_2) / (2\kappa_2) - \exp(-\kappa_1 \zeta_c) (\zeta_c + \kappa_1^{-1}) / \kappa_1 + \exp(-\kappa_2 [1 - \zeta_c]^2) / (2\kappa_2) - R / A_1 = 0$$
 (S-16c)

using bisection, with R equaling a random number. Eq S-16c is based on a transformation of random numbers into an arbitrary distribution<sup>4</sup> (here, into eq S-16a).

Asymmetric  $f(\zeta)$ . The asymmetric migration-time distribution is

$$f(\zeta) = A_2 \zeta \exp(-\kappa_3 \zeta) \tag{S-17a}$$

with  $\kappa_3$  equaling a constant (in the main article,  $\kappa_3 = 3.5$ ). The normalization constant  $A_2$  is

$$A_{2} = \left\{ \left[ 1 - \exp(-\kappa_{3}) \right] / \kappa_{3}^{2} - \exp(-\kappa_{3}) / \kappa_{3} \right\}^{-1}$$
 (S-17b)

A peak migration time  $\zeta_c$  was determined by solving

$$[1 - \exp(-\kappa_3 \zeta_c)] / \kappa_3^2 - \zeta_c \exp(-\kappa_3 \zeta_c) / \kappa_3 - R / A_2 = 0$$
 (S-17c)

using bisection, with R equaling a random number. Eq S-17c is based on the same transformation as eq S-16c.

Constant  $f(\zeta)$ . The constant migration-time distribution is

$$f(\zeta) = 1 \tag{S-18a}$$

A peak migration time  $\zeta_c$  was determined as

$$\zeta_c = R \tag{S-18b}$$

with R equaling a random number.

# Part 5. Least square fits to graphs of $\alpha_t$ , $\alpha_{e,t}$ , and $\log(\overline{m}_t)$ vs $\log(\sigma / X)$

The fits are mentioned in the main article at the end of the section, "Threshold Values of  $\overline{p}$  versus  $\overline{m}$  Curve", in the Results and Discussion. Let  $s = \log(\sigma/X)$ . The graphs in Figure 3a of the main article can be estimated from the polynomial fits

$$\alpha_t = -0.9530 - 0.9848s - 0.1442s^2 - 0.007830s^3$$
 (S-19)

$$\alpha_{e,t} = -1.423 - 1.287s - 0.0877s^2 \tag{S-20}$$

$$\log(\bar{m}_t) = -1.986 - 1.949s - 0.1718s^2 - 0.01102s^3$$
 (S-21)

with correlation coefficients of 0.99998 or larger.

### References

- 1. Davis, J.M.; Carr, P.W. Anal. Chem. 2009, 81, 1198-1207.
- Bevington, P.R. Data Reduction and Error Analysis for the Physical Sciences; McGraw Hill Book Company: New York, 1969, pp. 56-60.
- Dahlquist, G.; Bjorck, A. Numerical Methods; Prentice-Hall, Inc.: Englewood Cliffs, NJ, 1974, p. 453.
- 4. *Ibid.*, p. 452.

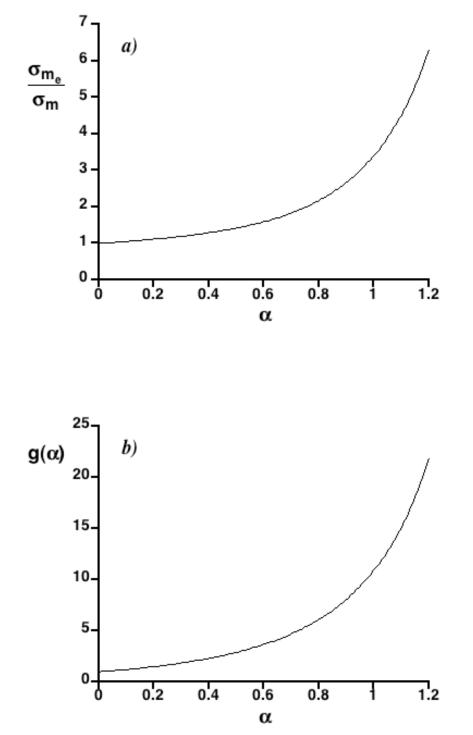
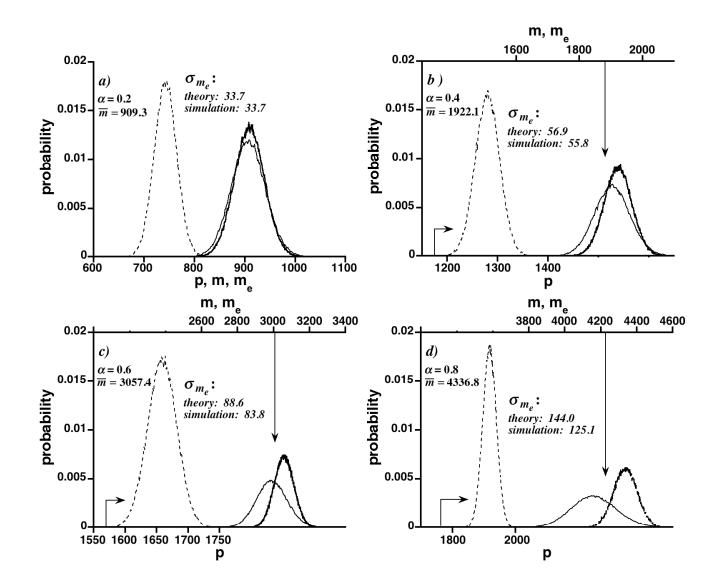


Figure S-1. a) Graph of  $\sigma_{m_e} / \sigma_m$  vs saturation  $\alpha$  (eq S-14). b) Graph of  $g(\alpha)$  vs  $\alpha$  (eq S-11b), with  $R_s^*$  equal to eq 4c of the main article.



Caption on next page

Figure S-2. Graphs of discrete probability distributions vs p, m, and  $m_e$ , as determined by Monte-Carlo simulations (p, m) and solutions to eqs S-2 and S-3 ( $m_e$ ) in Part 2 of the Supporting Information. Dashed, bold, and normal-weight curves are the p, m, and  $m_e$  distributions, respectively. In b) – d) different abscissas are used for p, and for mand  $m_e$ , to reduce unused space.  $\sigma/X = 8 \times 10^{-5}$ . a)  $\alpha = 0.2$ . b)  $\alpha = 0.4$ . c)  $\alpha = 0.6$ . d)  $\alpha = 0.8$ .