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神経線維伝導速度分布の blind deconvolution

Satoshi HONDA 本多 敏

Dept. of Appl. Phys. & Physico-Inform., Keio Univ.
honda@appi.keio.ac.jp

inverse problems & measurement

- problems of finding and characterizing unknown parameters and structures by indirect measurements.
- cover wide range of engineering applications, such as computed tomography, non-destructive inspection, non-invasive measurements, shape design, and so on.

inverse problems & **measurement**

- process of experimentally obtaining information about the magnitude of a **quantity**

NOTES

- 1 Measurement implies a **measurement procedure**, based on a theoretical model.
- 2 In practice, measurement presupposes a calibrated **measuring system**, possibly subsequently verified.

International Vocabulary of Basic and General Terms in Metrology (VIM)

TOMOGRAPHIC METHOD IN MEASUREMENT SYSTEM

Forward problem:

$$f(\mathbf{x}) \xrightarrow{\text{measurement}} \rho(\boldsymbol{\xi})$$

Inverse problem:

$$\rho(\boldsymbol{\xi}) \xrightarrow{\text{reconstruction}} \hat{f}(\mathbf{x})$$

Integral Formulation

$$\rho(\boldsymbol{\xi}) = \int_{\Omega} f(\mathbf{x}) d\Omega$$

$$\rho(\boldsymbol{\xi}) = \mathcal{R}\{f(\mathbf{x})\}$$

$$\exists |\mathcal{R}^{-1}\{\rho(\boldsymbol{\xi})\} \Rightarrow f(\mathbf{x})$$

Well-Conditioned/Posed

1. existence
2. uniqueness
3. smoothness

Example: CT

$$\begin{aligned}\rho(\boldsymbol{\xi}) &= \rho(\theta, u) = \int_L f(\mathbf{x}) ds \\ f(x, y) &= \frac{1}{2\pi^2} \int_0^\pi \int_{-R}^R \frac{1}{x \cos \theta + y \sin \theta - u} \frac{\partial \rho}{\partial u} du d\theta \\ &= \mathcal{R}^{-1}\{\rho(\theta, u)\}\end{aligned}$$

Reconstruction:

$$\operatorname{argmin}_{f \in \mathcal{H}_1} \|Kf - g\| = \hat{f}$$

$$\iff K^*K\hat{f} = K^*g \iff K\hat{f} = Pg \iff \hat{f} = K^\dagger g$$

$$K^\dagger : \text{bounded} \iff \#\{\lambda_n\} < \infty \longrightarrow \text{ill-posed}$$

Regularization:

$$\exists (K + \alpha I)^{-1} : \text{bounded}$$

$$\|Kf - g\|^2 + \alpha \|f\|^2 \rightarrow \min$$

$$\|Kf - g\|^2 + R(f; \alpha) \rightarrow \min$$

Projection Onto Convex Sets:

$$f_0 \in \mathcal{C}_0 \cap \left(\bigcap_{i=1}^m \mathcal{C}_i \right)$$

$$T = P_m P_{m-1} \cdots P_1, \quad P_i : \mathcal{H} \rightarrow \mathcal{C}_i, \quad T^n f \rightarrow f_0$$

Regularization: 正則化 (最適化問題)

正則化パラメータの決定法

L-curve 法

最適パラメータ決定理論

観測ノイズが必要

ベイジアンモデルによるハイパーパラメータ推定 (MAP推定)

...

...

POCS: 凸射影法 (非線形反復法)

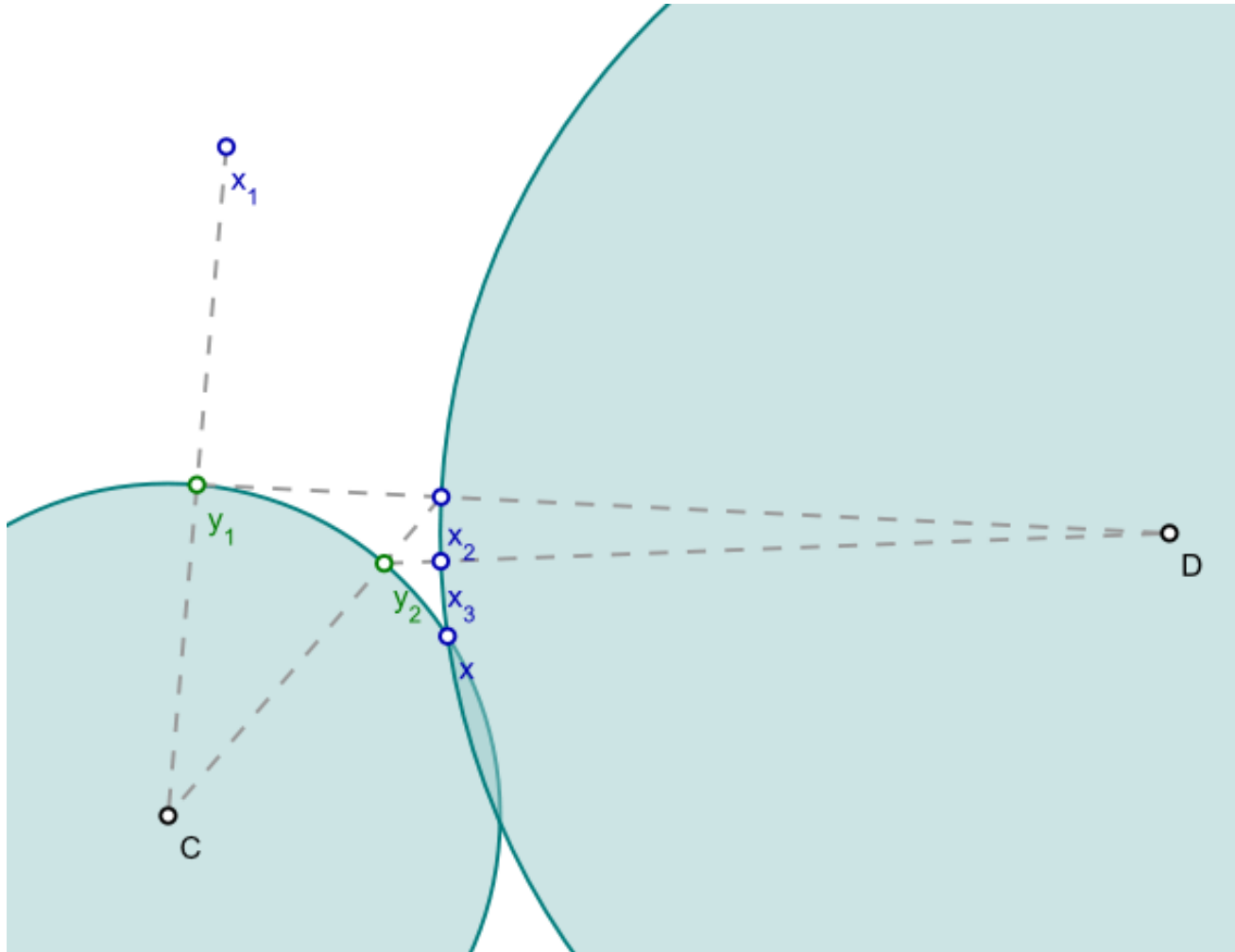
反復アルゴリズムの収束性

制約条件 (先験情報) の設定法

凸集合の境界に収束

制約条件が有効

alternate Projection Onto Convex Sets method



神経線維伝導速度分布の blind deconvolution



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Estimation of the conduction velocity distribution of human sensory nerve fibers

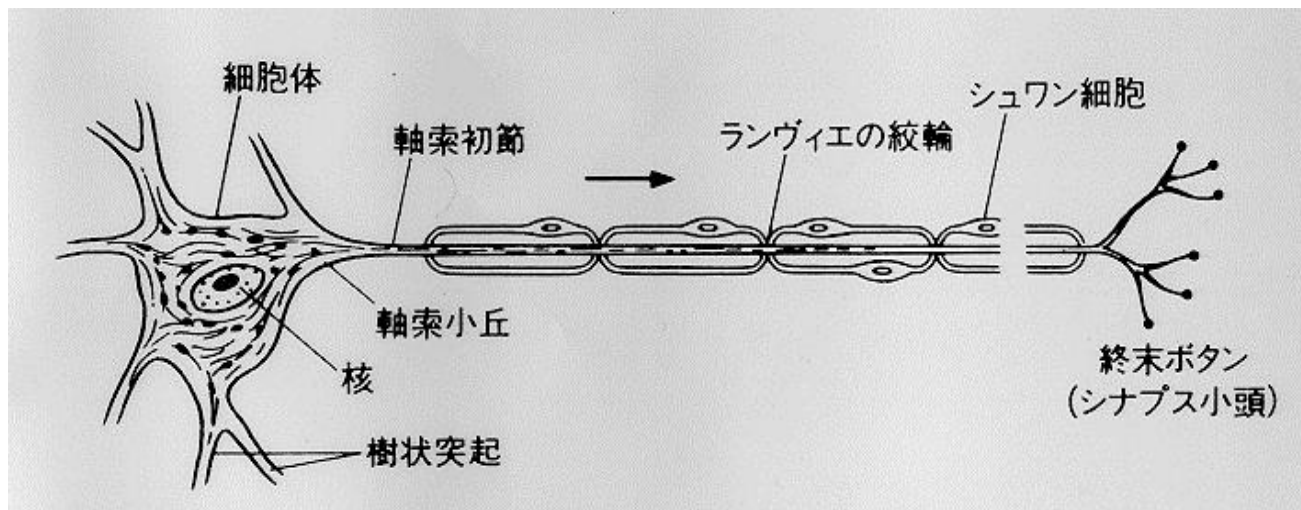
G. Morita ^a, Y.X. Tu ^a, Y. Okajima ^b, S. Honda ^{a, c, *}, Y. Tomita ^{a, b}

^a Faculty of Science and Technology, Keio University, 3-14-1, Hiyoshi, Kohoku-ku, Yokohama, Kanagawa 223-8522, Japan

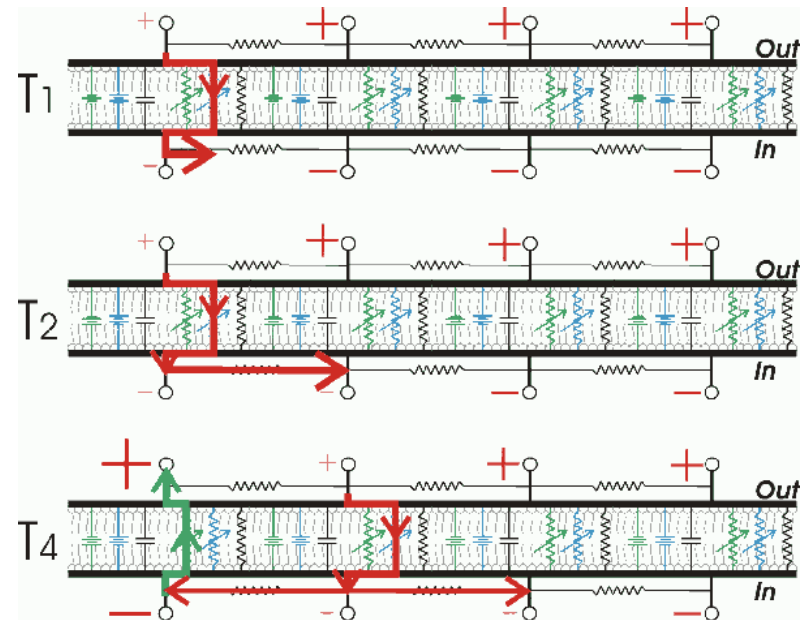
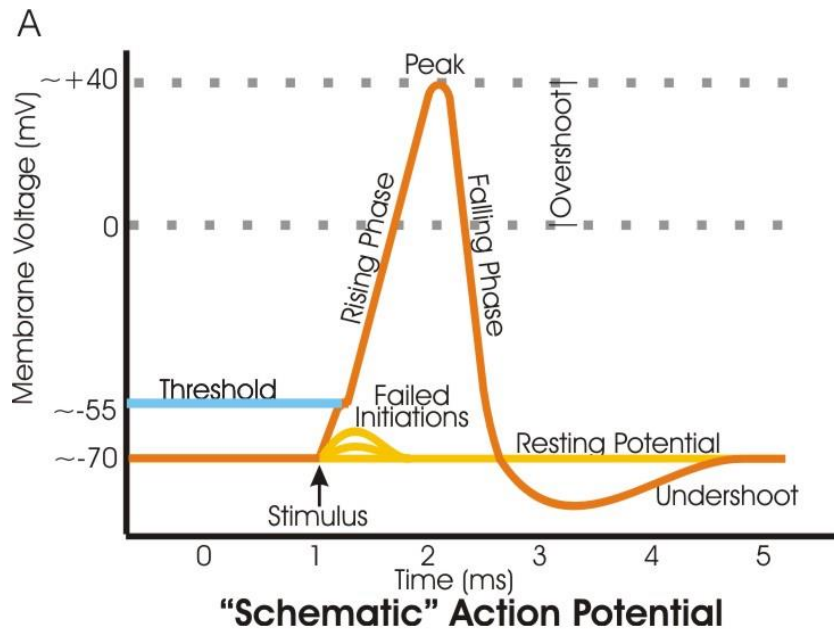
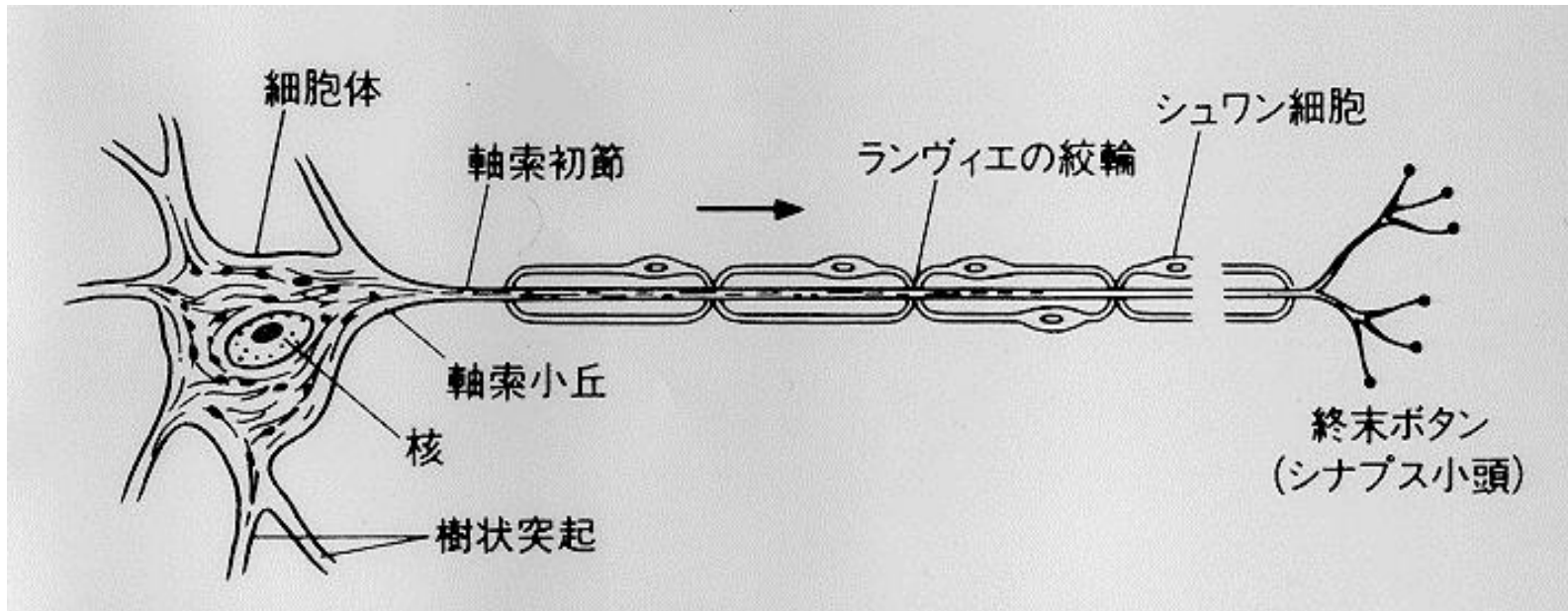
^b Tsukigase Rehabilitation Center, Keio University, 3-14-1, Hiyoshi, Kohoku-ku, Yokohama, Kanagawa 223-8522, Japan

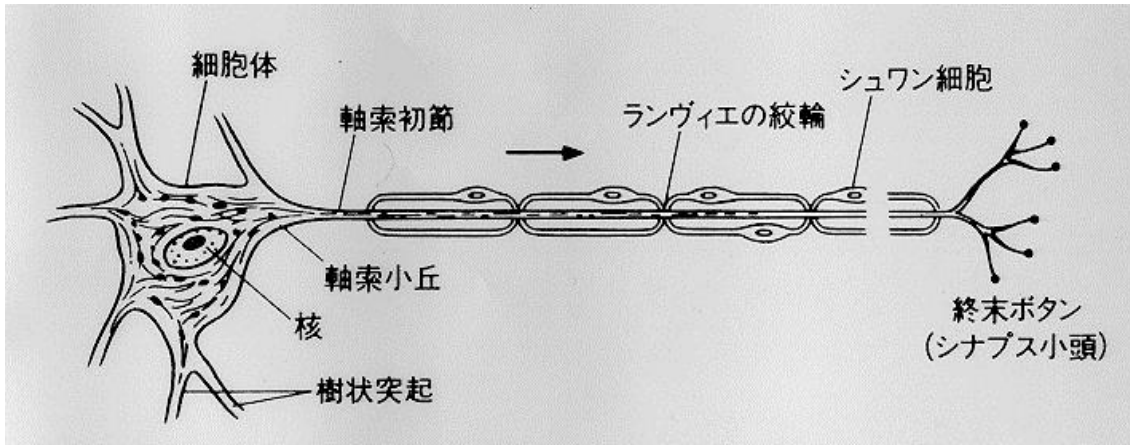
^c CREST, Japan Science and Technology Corporation, Kanagawa, 2-8-12, Iwamoto, Chiyoda-ku, Tokyo 101-0032, Japan

Received 5 June 2000; received in revised form 16 July 2001; accepted 21 August 2001

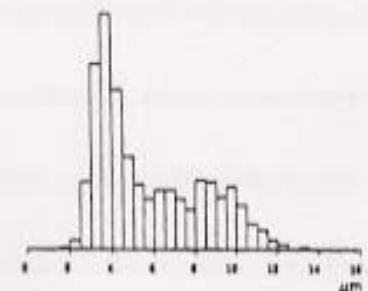
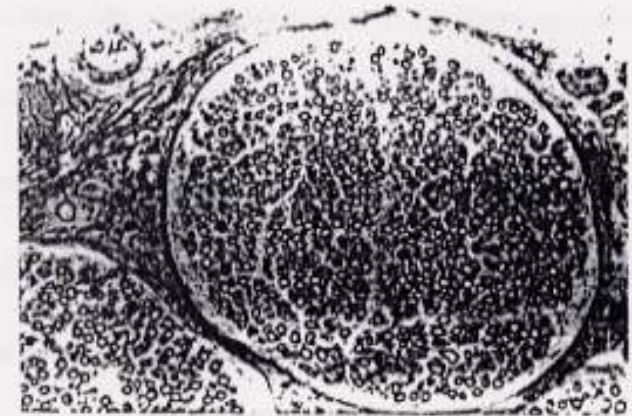
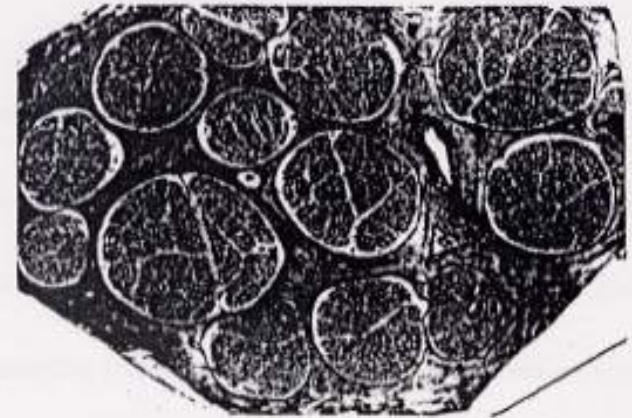
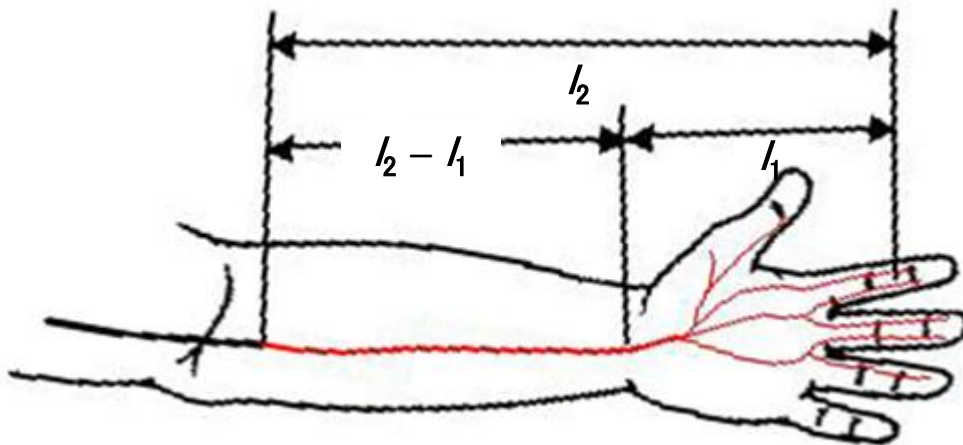


神経線維伝導速度分布の blind deconvolution



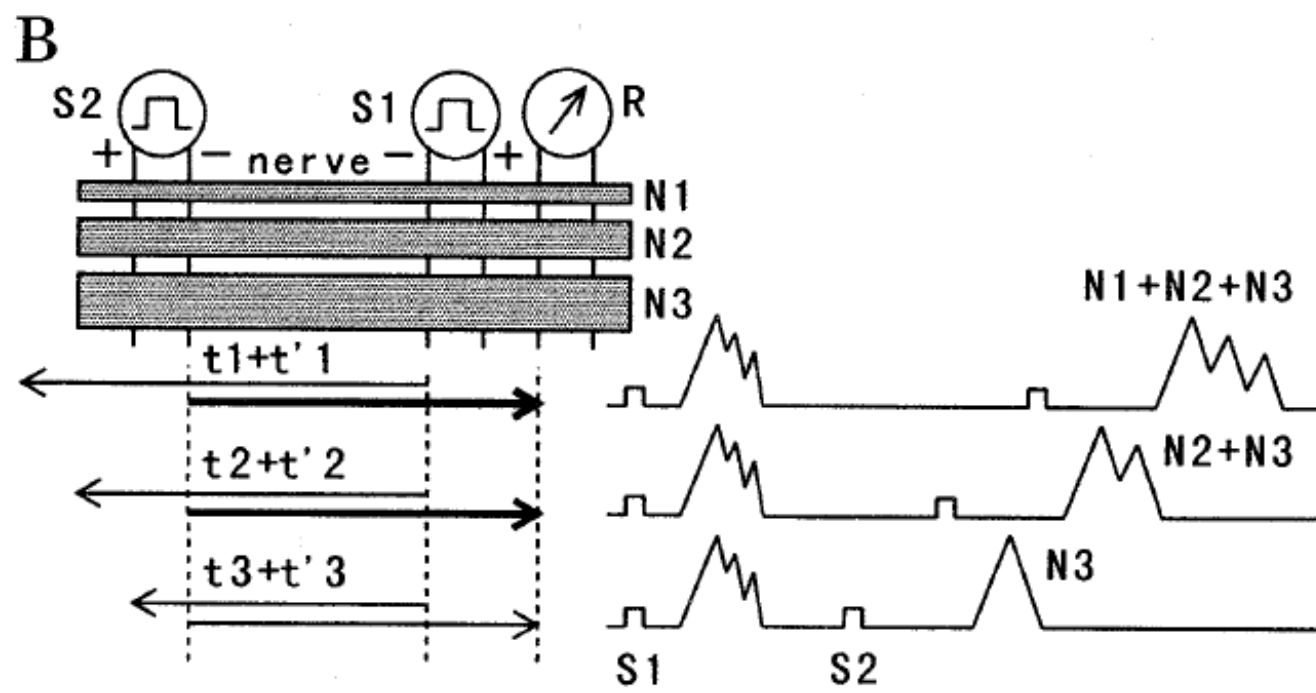
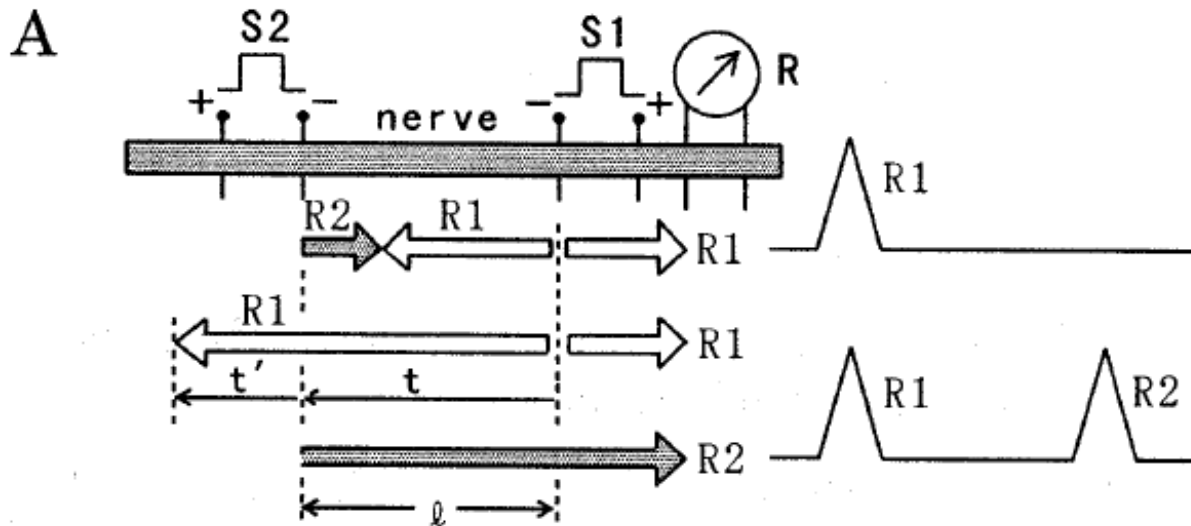


diabetes, heavy-metal poisoning
 → decrease in conduction velocity
 amyelination

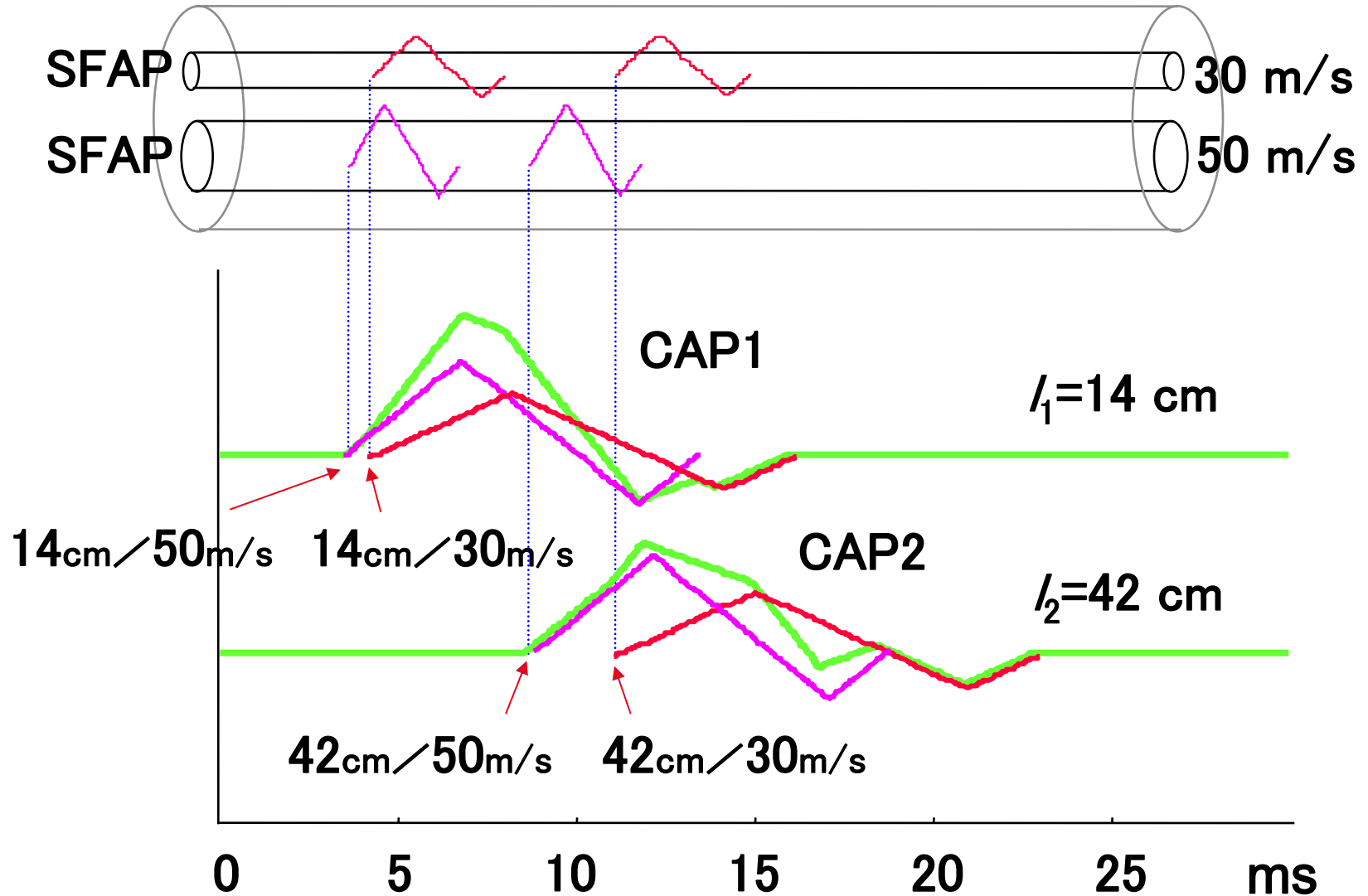


c

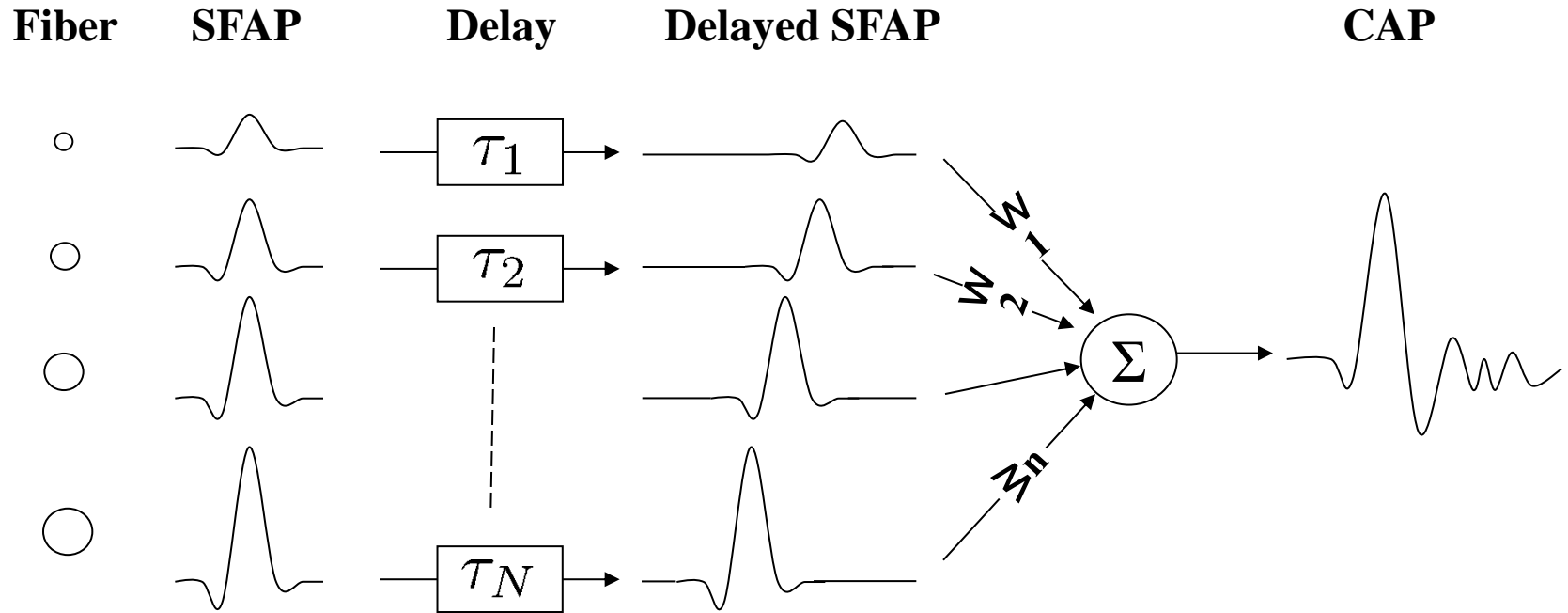
Collision Method



Single Fiber & Compound Action Potential



モデルの構築



$$y(t_i) = \sum_{j=1}^N A v_j^2 w(v_j) s\left(t_i - \frac{l}{v_j}\right)$$

$y(t_i)$: CAP

$s(t_i)$: SFAP

$w(v_j)$: CVD

1. Linear superposition
2. Independent propagation
3. Simultaneous activation at the same position
4. Constant velocity proportional to the diameter
5. Same duration
6. Amplitude proportional to fiber cross section

Linear CAP model:

$$y(t) = \int_0^{\infty} A v^2 w(v) s \left(t - \frac{l}{v} \right) dv,$$

Formulation of the Problem

$$y(t) = \int_0^{\infty} Av^2 w(v) s(t - \frac{l}{v}) dv$$

$$\Downarrow \quad \tau \equiv l/v$$

$$y(t) = \int_0^{\infty} A \left(\frac{l}{\tau}\right)^2 w\left(\frac{l}{\tau}\right) s(t - \tau) \frac{1}{\tau^2} d\tau.$$

$$y(t) = \int_0^{\infty} p(\tau; w) s(t - \tau) d\tau \equiv [p(\cdot; w) * s](t)$$

$$p(\tau; w) \equiv \frac{Al^2}{\tau^4} w\left(\frac{l}{\tau}\right)$$

$$y_i(t) = [p_i(\cdot; w) * s](t) + n_i(t), \quad i = 1, 2$$

$$H_1(\beta\omega)=H_2(\omega) \quad (4)$$

where $\beta=l_2/l_1>1$.

Taking into account (4), we write (2) in frequency domain, for two CAP's, $C_1(\omega)$ and $C_2(\omega)$, and after some manipulation, we obtain

$$H_1(\beta\omega) = \frac{C_2(\omega)}{C_1(\omega)} H_1(\omega) \quad (5)$$

In other words, (5) shows how the higher frequency components of $H_1(\omega)$ can be determined iteratively by the lower ones. Starting by an initial guess of $H_1(\omega/\beta^n) \cong H_1(0) = \text{cst} > 0$ (the integral of $h_1(\tau)$ is strictly positive), the following formula is derived

$$H_1(\omega) = \frac{C_2(\omega/\beta)}{C_1(\omega/\beta)} \frac{C_2(\omega/\beta^2)}{C_1(\omega/\beta^2)} \dots \frac{C_2(\omega/\beta^n)}{C_1(\omega/\beta^n)} H_1(\omega/\beta^n) \quad (6)$$

Formulation of the Problem

$$y(t) = \int_0^{\infty} Av^2 w(v) s\left(t - \frac{l}{v}\right) dv$$

$$\Downarrow \quad \tau \equiv l/v$$

$$y(t) = \int_0^{\infty} A \left(\frac{l}{\tau}\right)^2 w\left(\frac{l}{\tau}\right) s(t - \tau) \frac{1}{\tau^2} d\tau.$$

$$y(t) = \int_0^{\infty} p(\tau; w) s(t - \tau) d\tau \equiv [p(\cdot; w) * s](t)$$

$$p(\tau; w) \equiv \frac{Al^2}{\tau^4} w\left(\frac{l}{\tau}\right)$$

$$y_i(t) = [p_i(\cdot; w) * s](t) + n_i(t), \quad i = 1, 2$$

BLIND DECONVOLUTION

CAPs

$$\begin{aligned}y_1(t) &= (p_1 * s)(t) + n_1(t) \\y_2(t) &= (p_2 * s)(t) + n_2(t)\end{aligned}$$

Latency & DCV:

$$p_i(\tau) = \frac{Al_i^2}{\tau^4} w\left(\frac{l_i}{\tau}\right) = \frac{A}{l_i^2} v^4 w(v), \quad i = 1, 2$$

Blind Deconvolution Problem:

$$J(s, w; l_1, l_2) \equiv \|y_1 - p_1(\cdot; w) * s\|^2 + \|y_2 - p_2(\cdot; w) * s\|^2 \rightarrow \text{minimize}$$

Two Stage Algorithm:

$$[\tilde{s}(t; l_1, l_2), \tilde{w}(v; l_1, l_2)] = \underset{s, w}{\operatorname{argmin}} J(s, w; l_1, l_2)$$

... GPOCS – RNLS & WF

$$[\hat{l}_1, \hat{l}_2] = \underset{l_1, l_2}{\operatorname{argmin}} J(\tilde{s}(\cdot; l_1, l_2), \tilde{w}(\cdot; l_1, l_2); l_1, l_2)$$

... Fibonacci Search

$$\hat{s}(t) = \tilde{s}(t; \hat{l}_1, \hat{l}_2)$$

$$\hat{w}(v) = \tilde{w}(v; \hat{l}_1, \hat{l}_2)$$

$$y_1 = p_1(\cdot; w^{(k)}) * s^{(k+1)} + n_1$$

Regularized
NNLS

Projection
onto
 C_s

Projection
onto
 C_w

Wiener Filter

$$y_2 = p_2(\cdot; w^{(k+1)}) * s^{(k)} + n_2$$

$$C_w =$$

$$\{w(v) | w(v) \geq 0;$$

$$w(v) = 0, v \in [v_{\min}, v_{\max}]\},$$

$$C_s =$$

$$\{s(t) | s(t) = 0, t \in [0, T_0];$$

$$S(\omega) \simeq 0, \omega \in [\Omega_0, \infty]\},$$

$$y_1 = p_1(\cdot; w^{(k)}) * s^{(k+1)} + n_1$$

Regularized
NNLS

Projection
onto
 C_s



Projection
onto
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Wiener Filter

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$$y_1 = p_1(\cdot ; w^{(k)}) * s^{(k+1)} + n_1$$

Regularized
NNLS

Projection
onto
 C_s

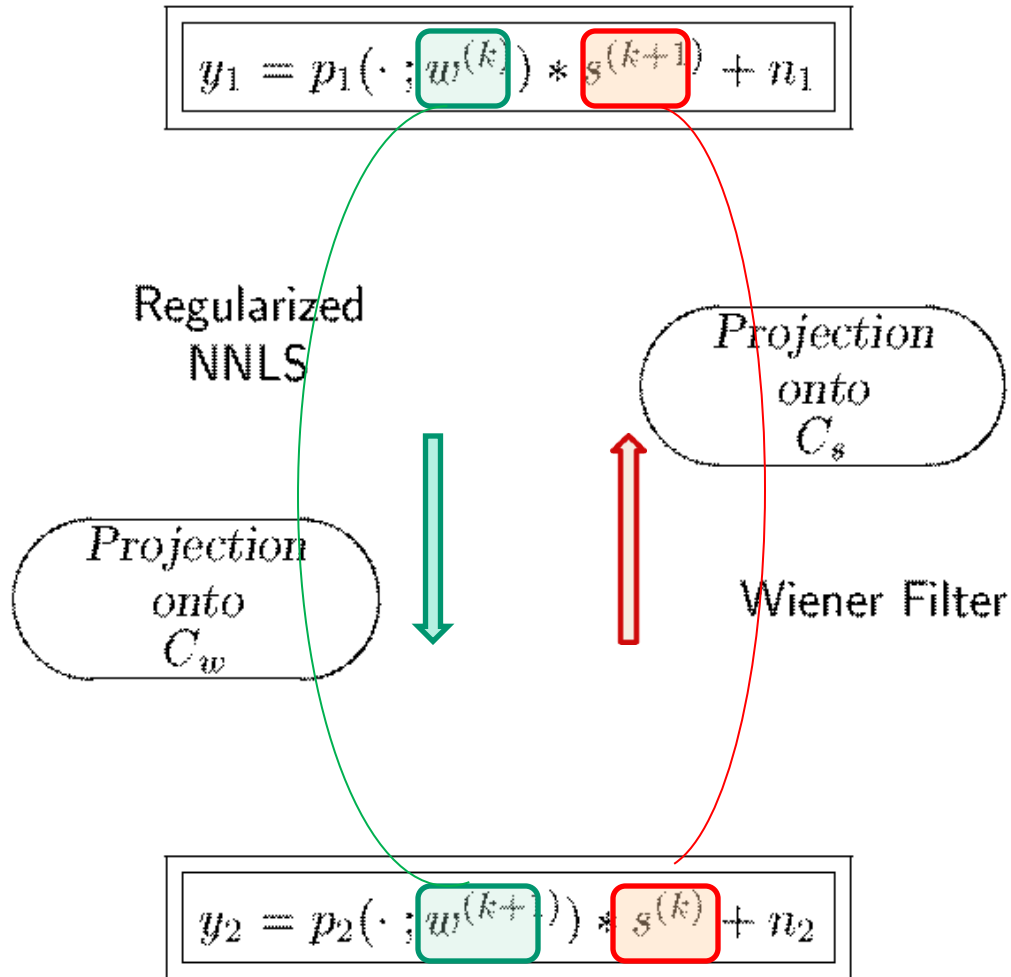
Projection
onto
 C_w

Wiener Filter

$$y_2 = p_2(\cdot ; w^{(k+1)}) * s^{(k)} + n_2$$

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Regularized NonNegative Least Square (RNNLS)

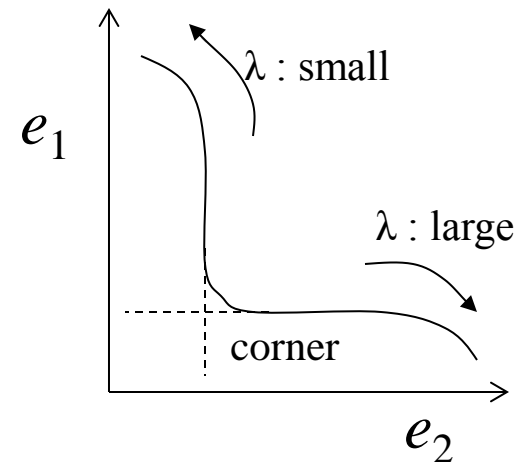
$$\mathbf{y} = \mathbf{A}\mathbf{w}$$

$$e = \underbrace{\|\mathbf{y} - \mathbf{A}\mathbf{w}\|^2}_{e_1} + \lambda \underbrace{\|\mathbf{C}\mathbf{w}\|^2}_{e_2} \quad \rightarrow \quad \min_{\mathbf{w} \geq 0}$$

L-curve

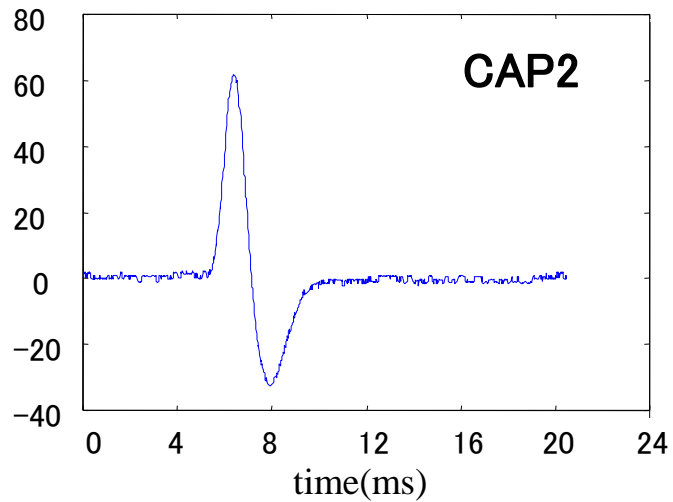
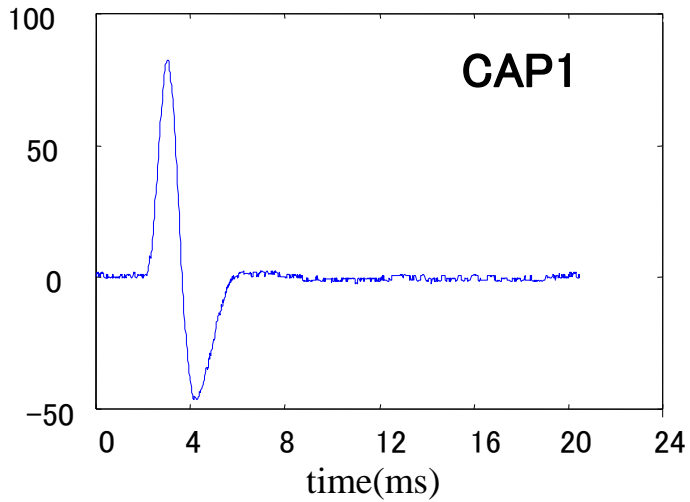
λ : regularization param.

\mathbf{C} : differential op.

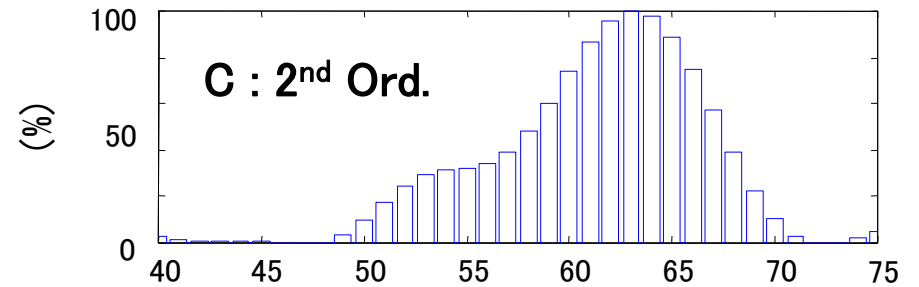
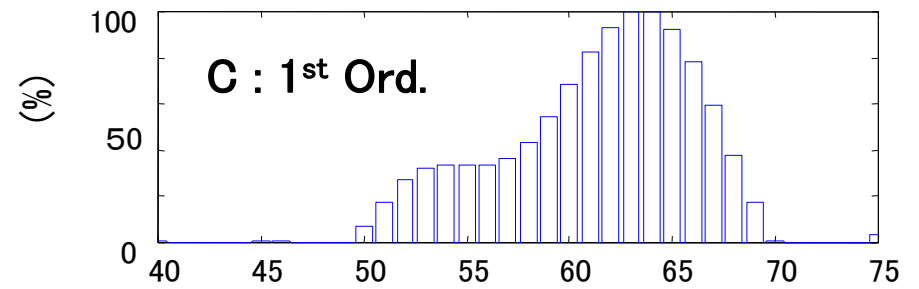
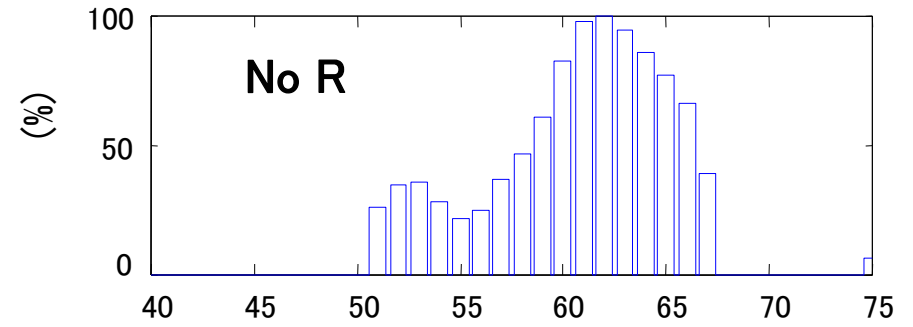


Effect of Differential Operators

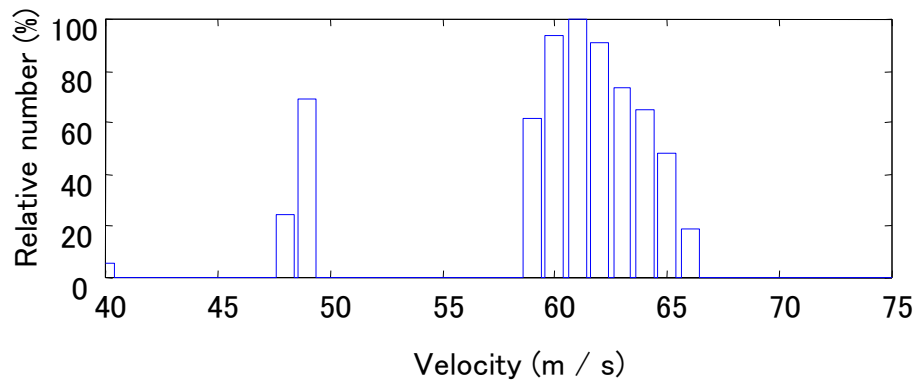
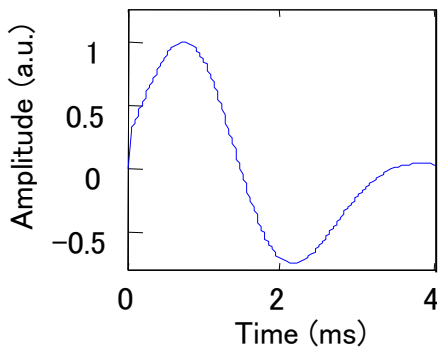
CAP



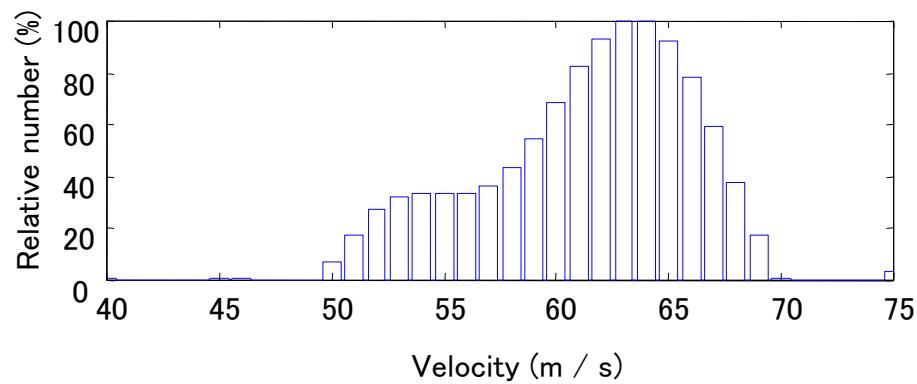
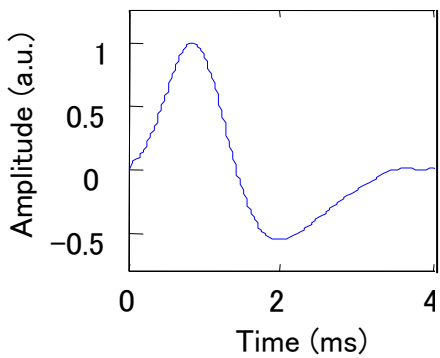
DCV



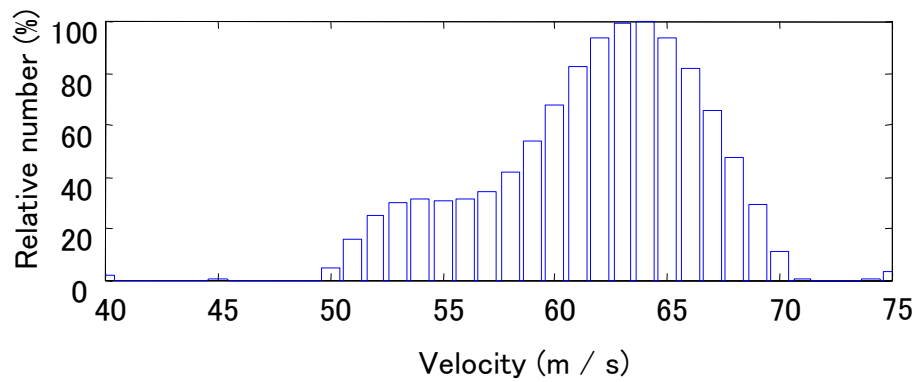
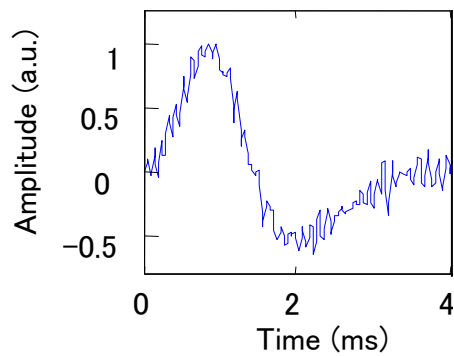
(A)



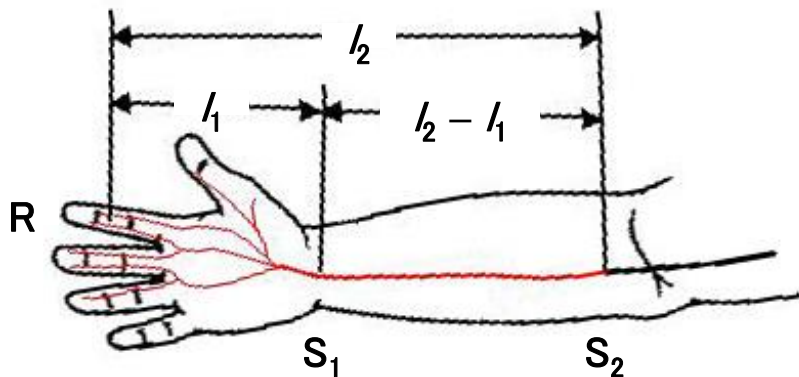
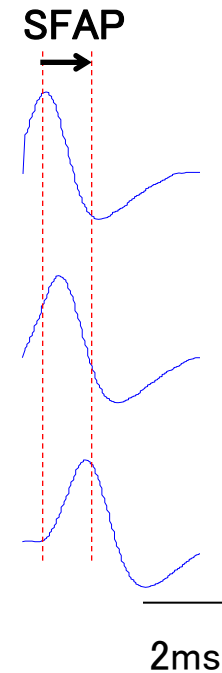
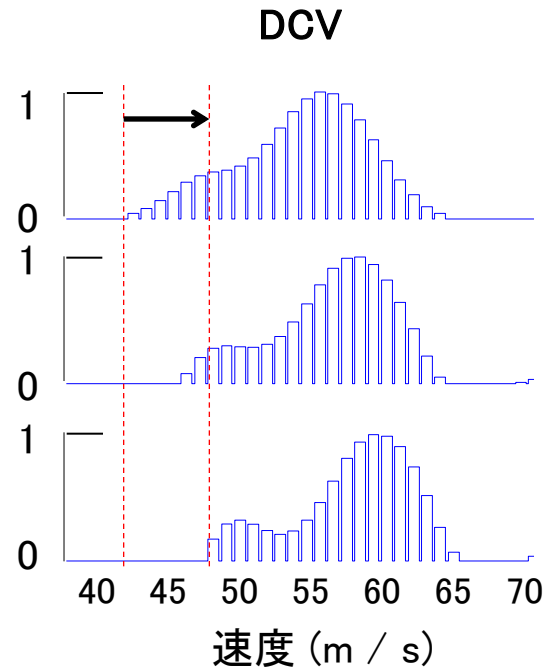
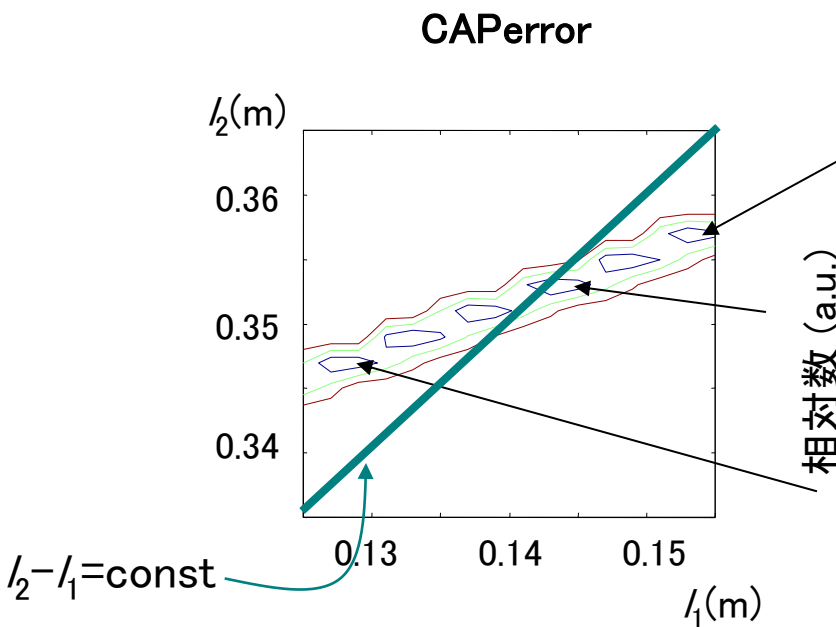
(B)



(C)



Optimal search of conduction length l_1 , l_2



- ① $l_2 - l_1 \leftarrow$ measured value
- ② search for l_1

Two Stage Algorithm:

$$[\tilde{s}(t; l_1, l_2), \tilde{w}(v; l_1, l_2)] = \underset{s, w}{\operatorname{argmin}} J(s, w; l_1, l_2)$$

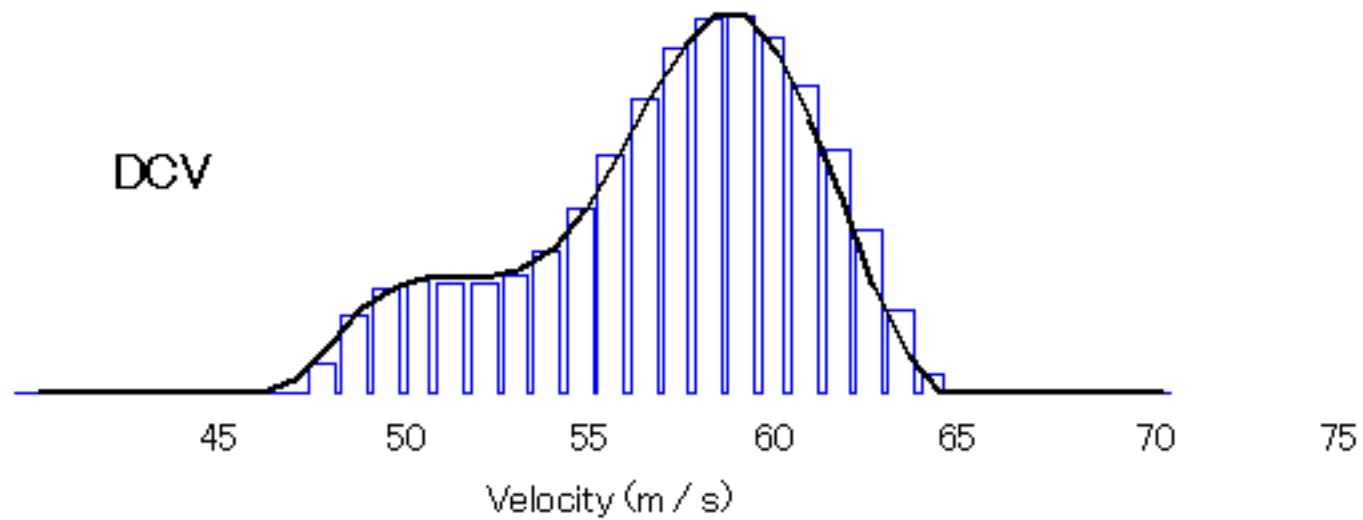
... GPOCS – RNNLS & WF

$$[\hat{l}_1, \hat{l}_2] = \underset{l_1, l_2}{\operatorname{argmin}} J(\tilde{s}(\cdot; l_1, l_2), \tilde{w}(\cdot; l_1, l_2); l_1, l_2)$$

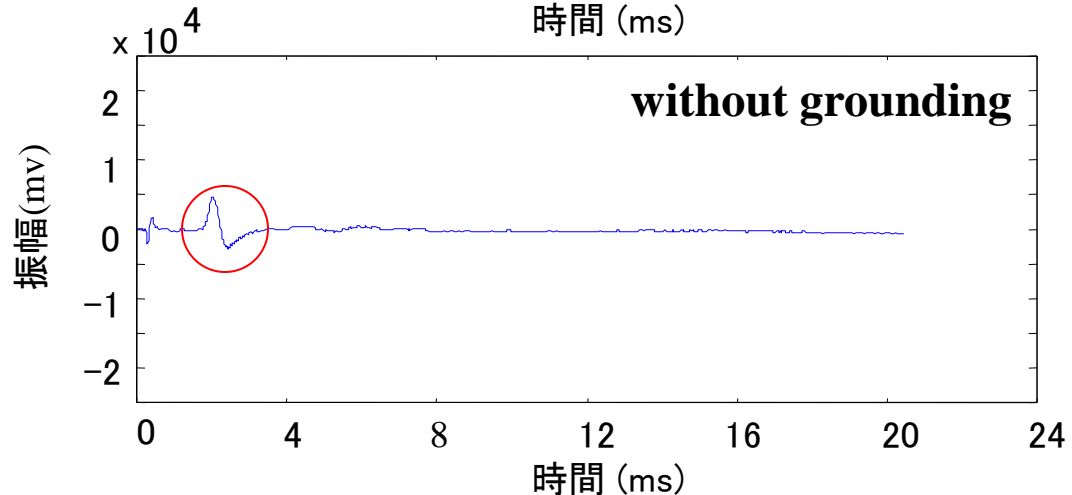
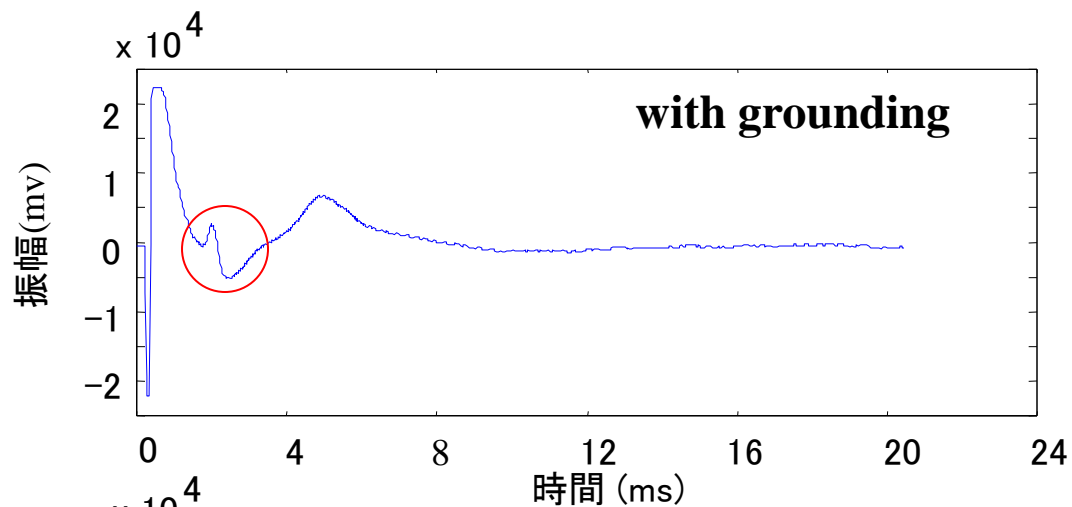
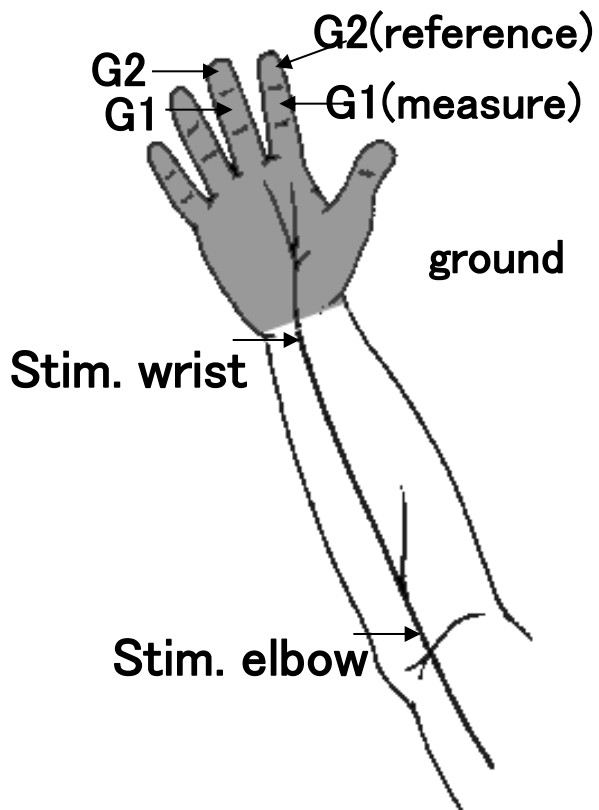
... Fibonacci Search

$$\hat{s}(t) = \tilde{s}(t; \hat{l}_1, \hat{l}_2)$$

$$\hat{w}(v) = \tilde{w}(v; \hat{l}_1, \hat{l}_2)$$



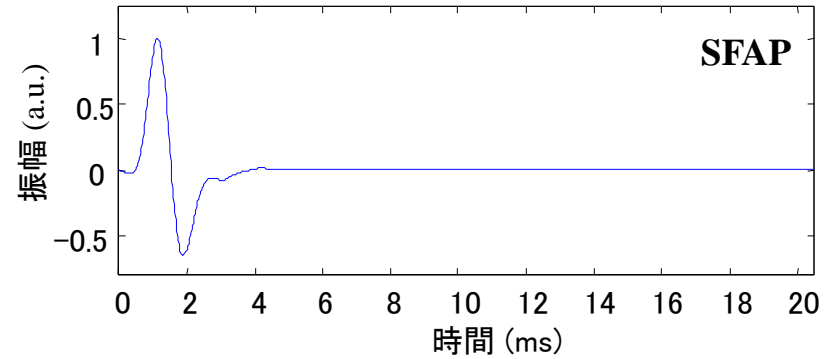
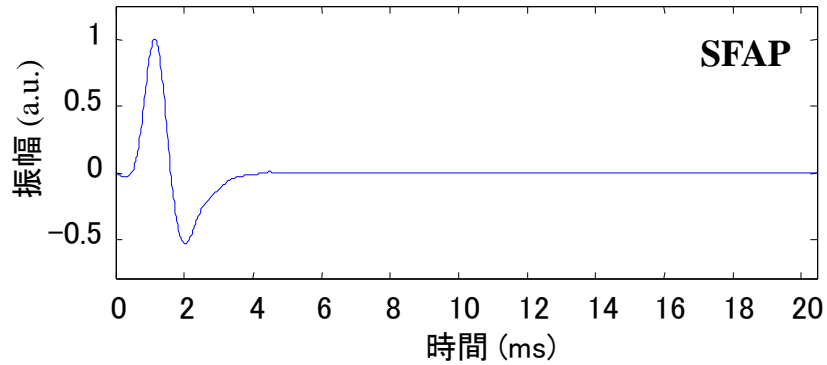
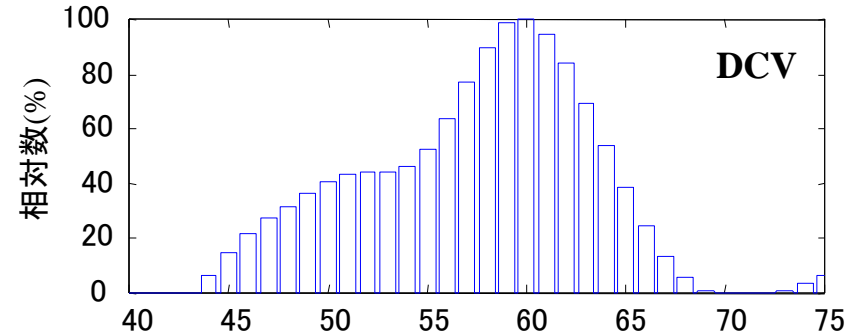
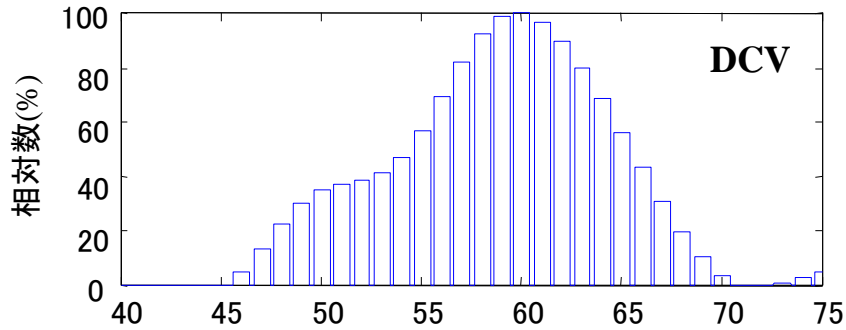
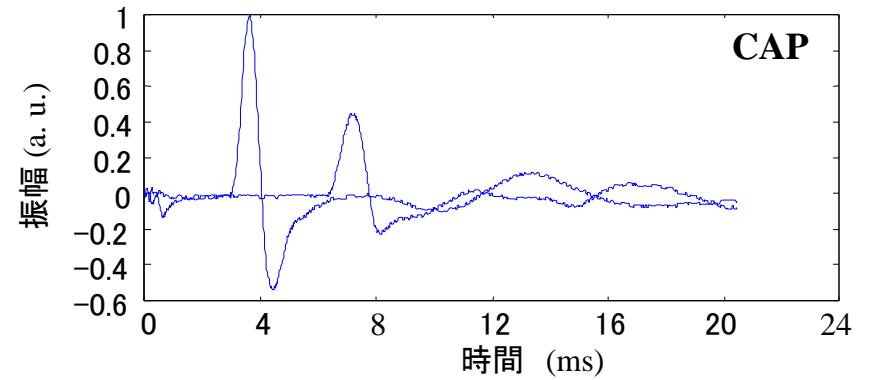
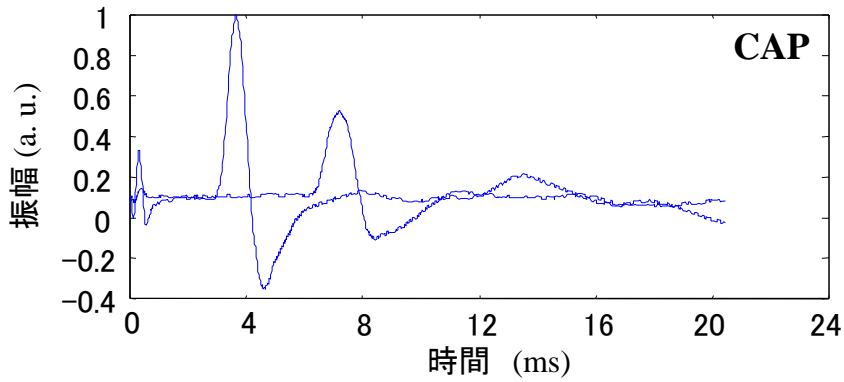
CAP計測における手のひらアースの効果



Sound subject

(#1)

corrcoeff.=0.969

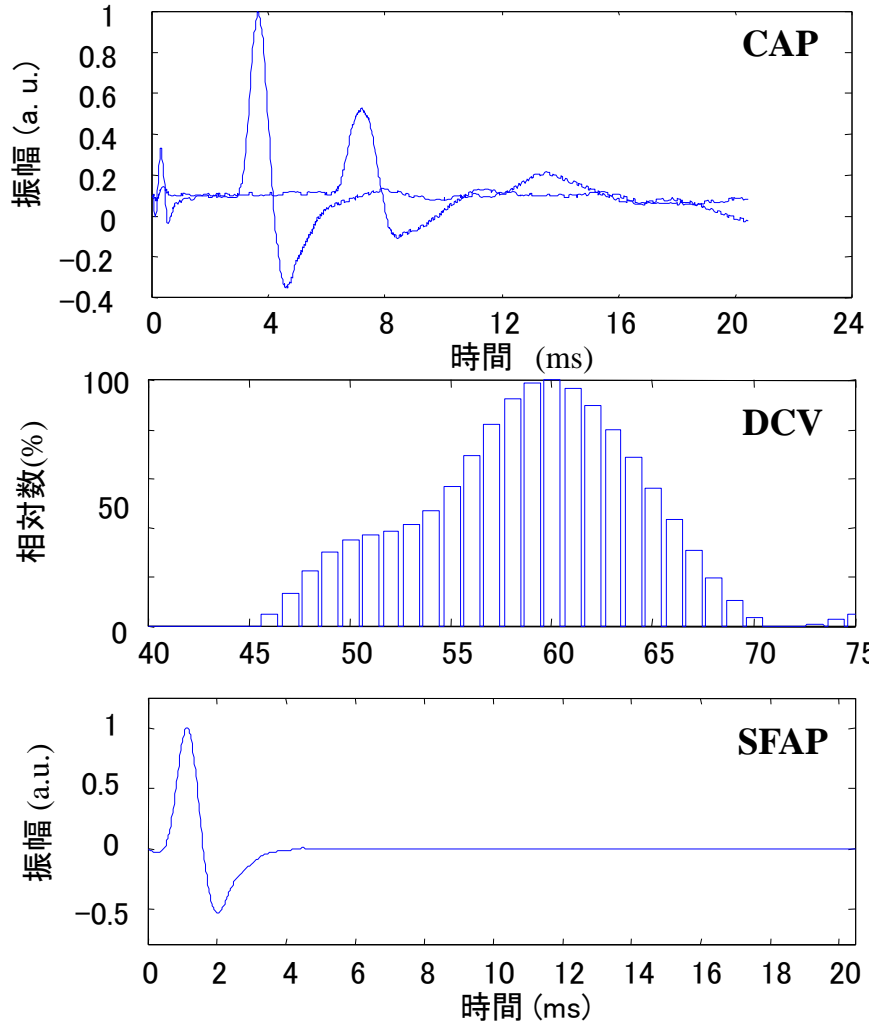


index finger

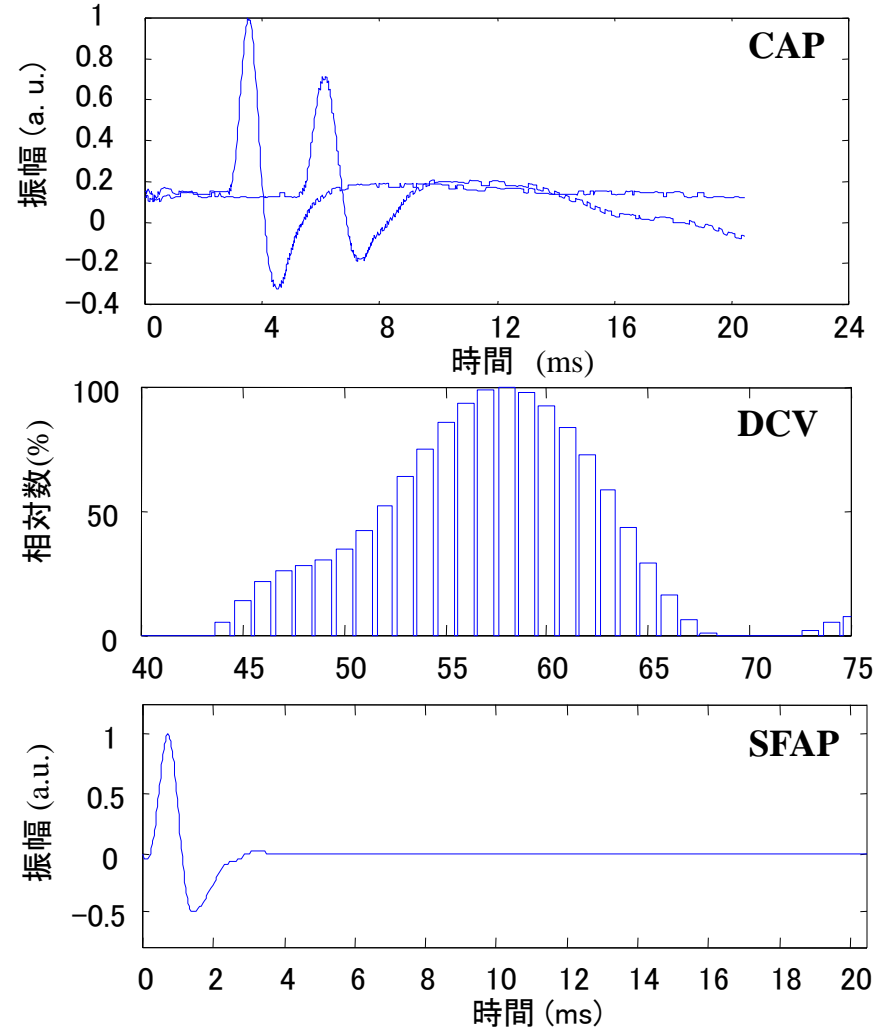
middle finger

Sound subject (#2)

corrcoef=0.909



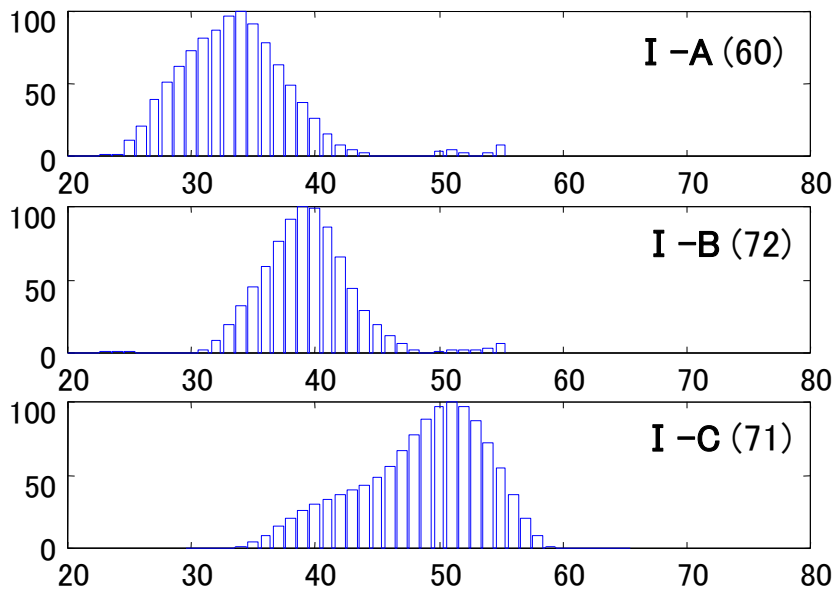
(A) 2000. Mar



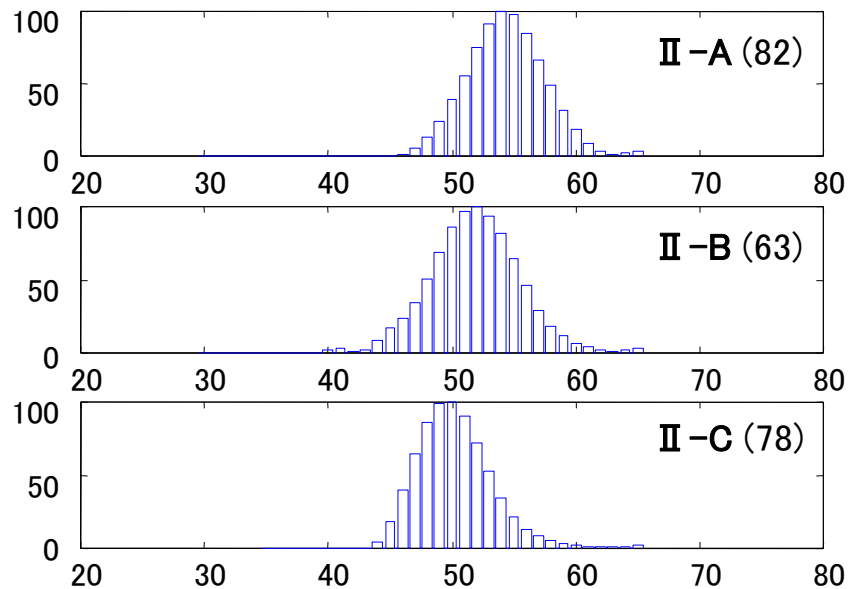
(B) 2000. Oct

CDV of diabetes patients

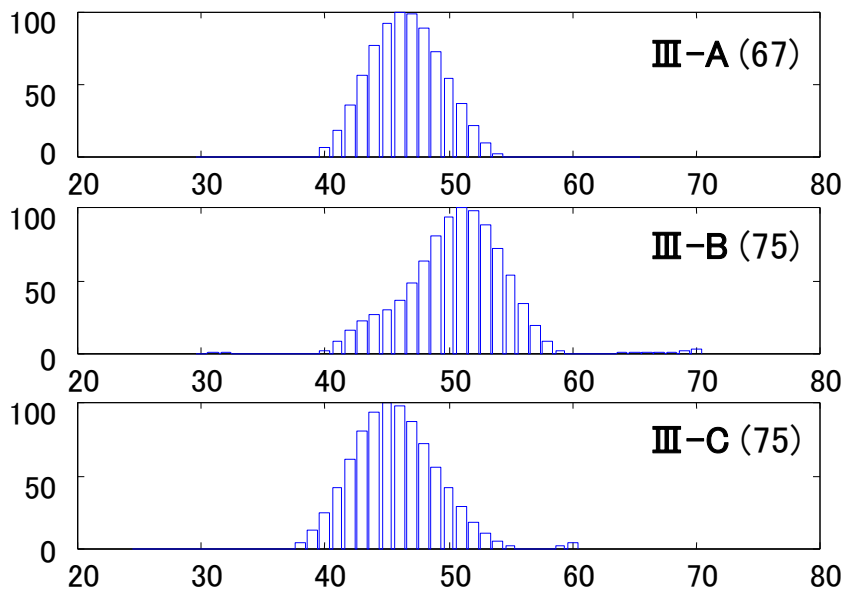
group I : diabetes with neural disorder



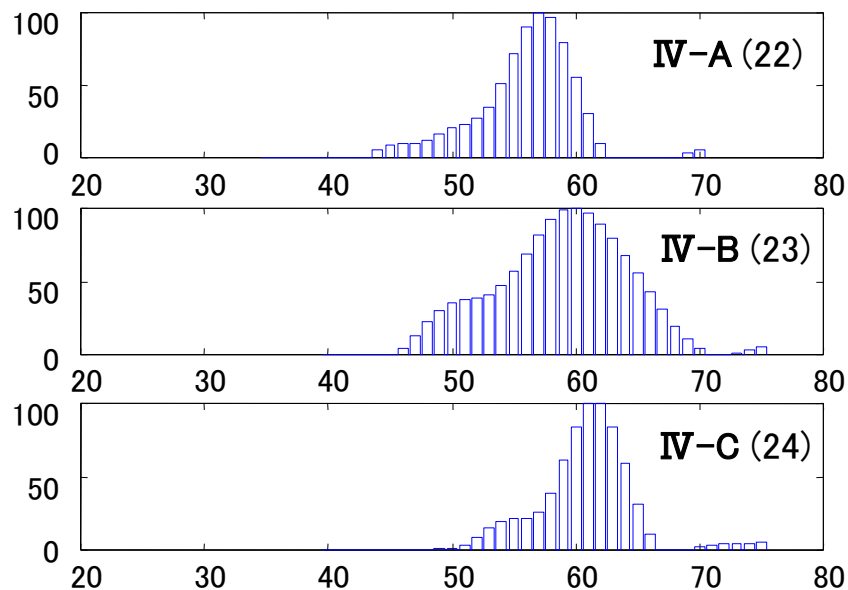
group II : diabetes without neural disorder



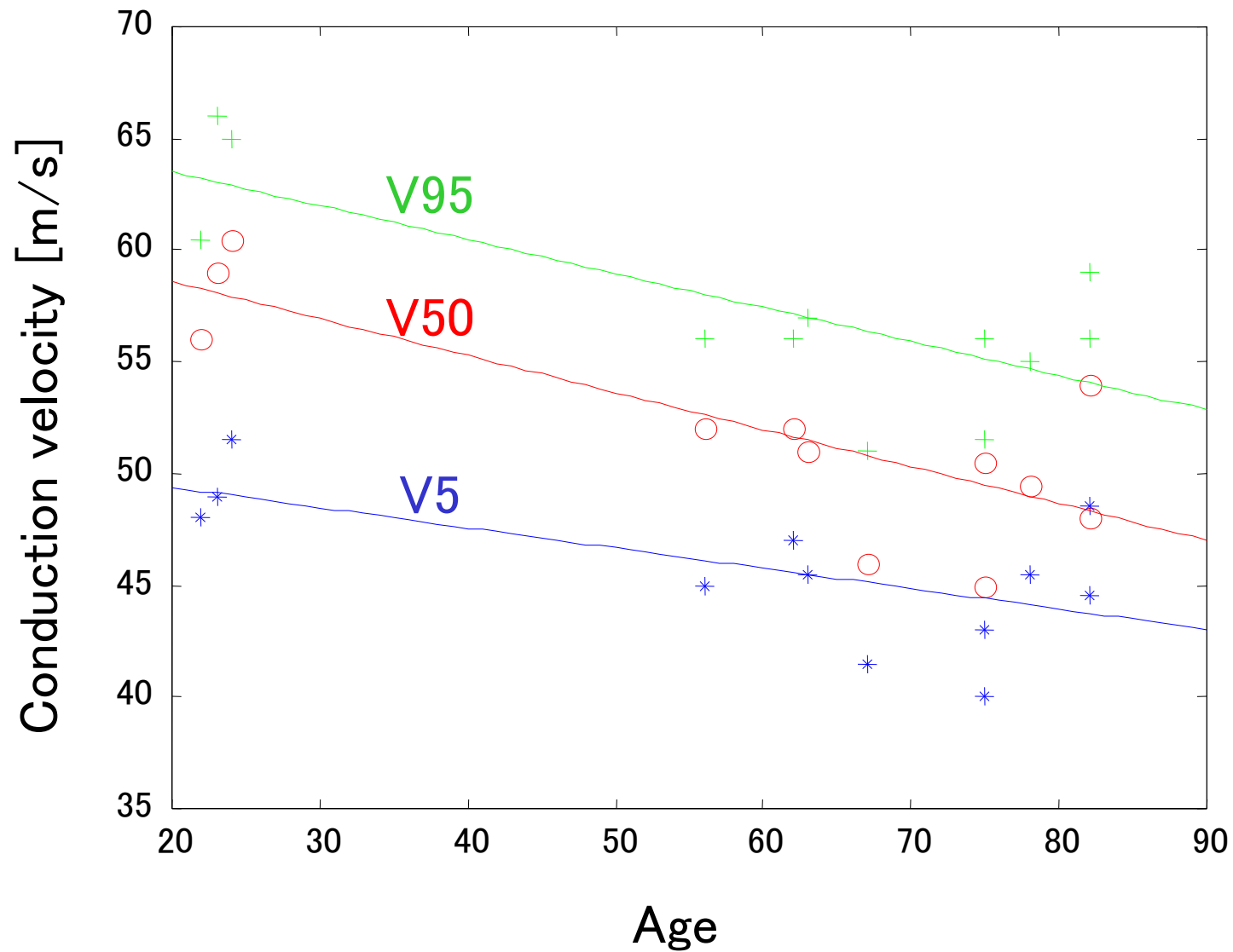
group III : sound(control)



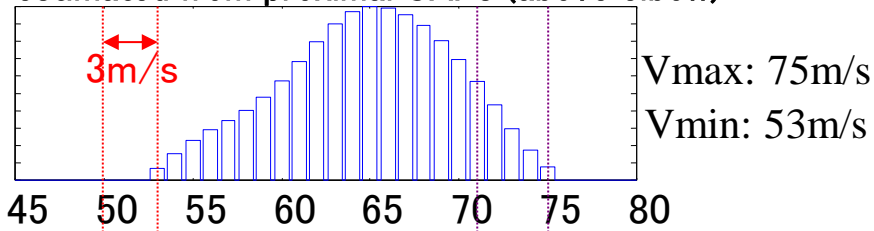
group IV : sound(youth)



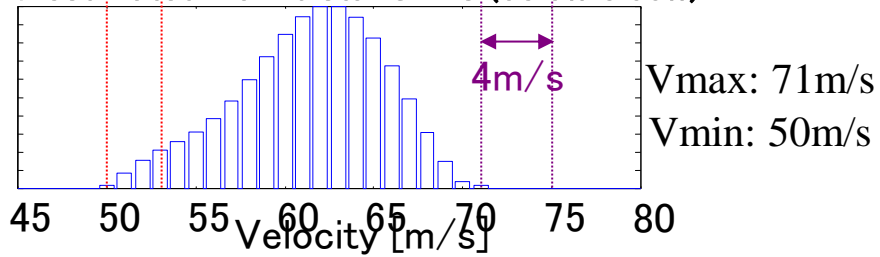
Aging of CVD



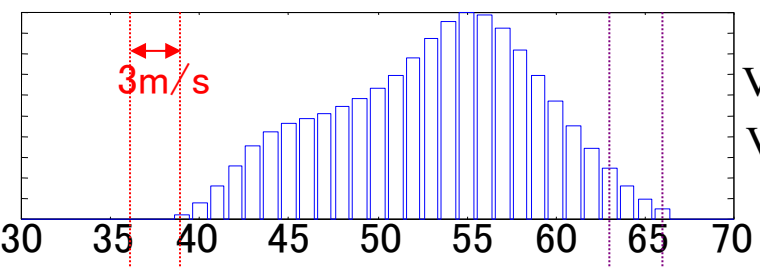
DCV estimated from proximal CAPs (above elbow)



DCV estimated from distal CAPs (below elbow)

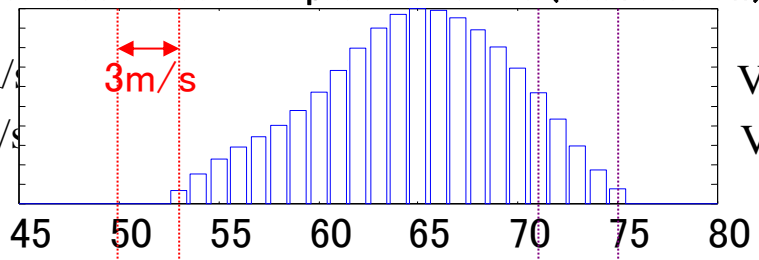


DCV estimated from proximal CAPs (above elbow)



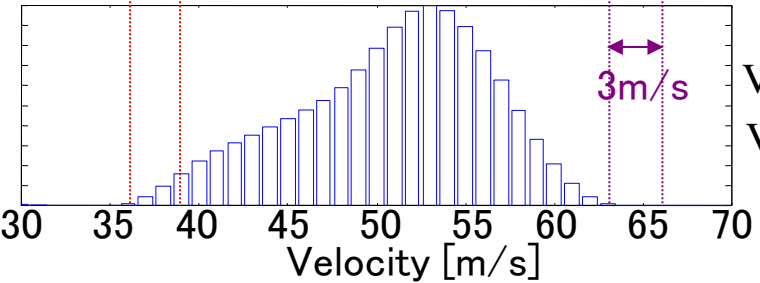
$V_{max}: 66\text{m/s}$
 $V_{min}: 39\text{m/s}$

DCV estimated from proximal CAPs (above elbow)



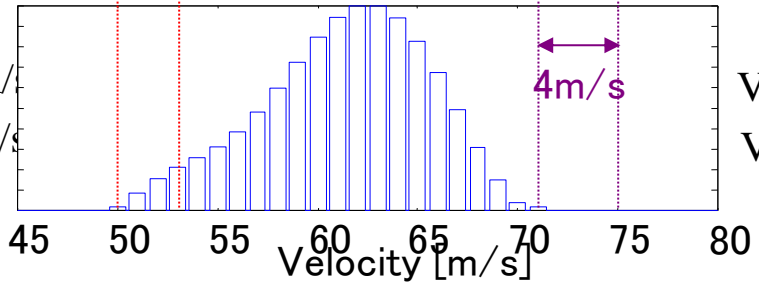
$V_{max}: 75\text{m/s}$
 $V_{min}: 53\text{m/s}$

DCV estimated from distal CAPs (below elbow)

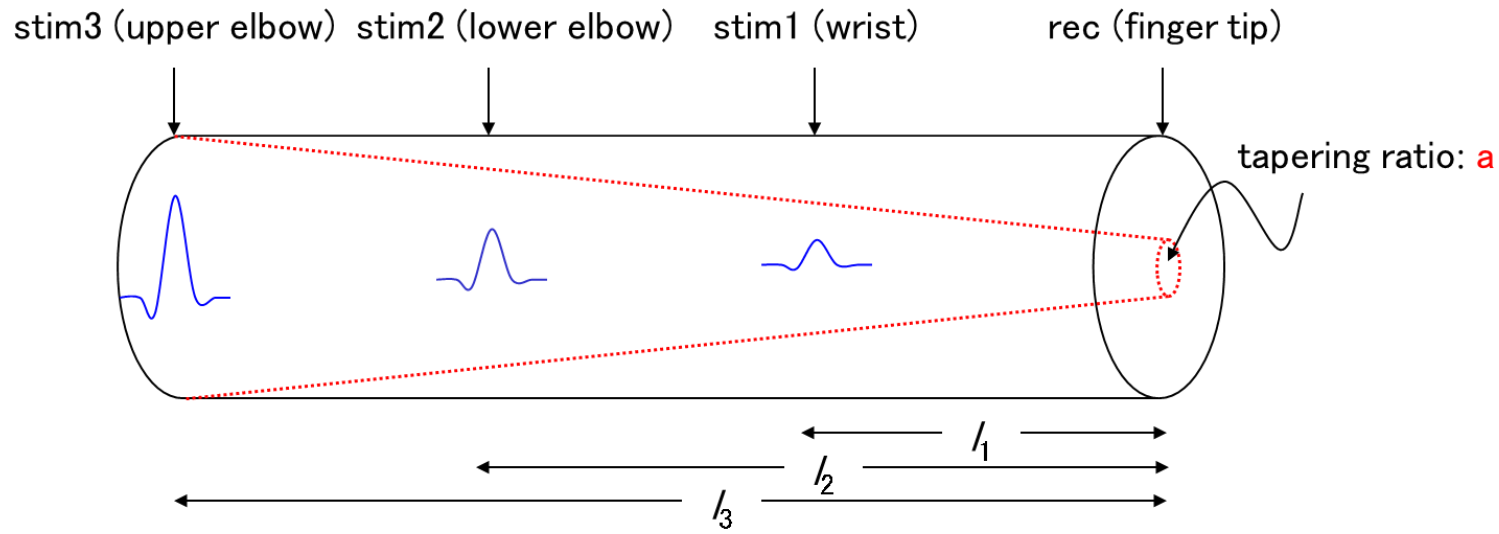


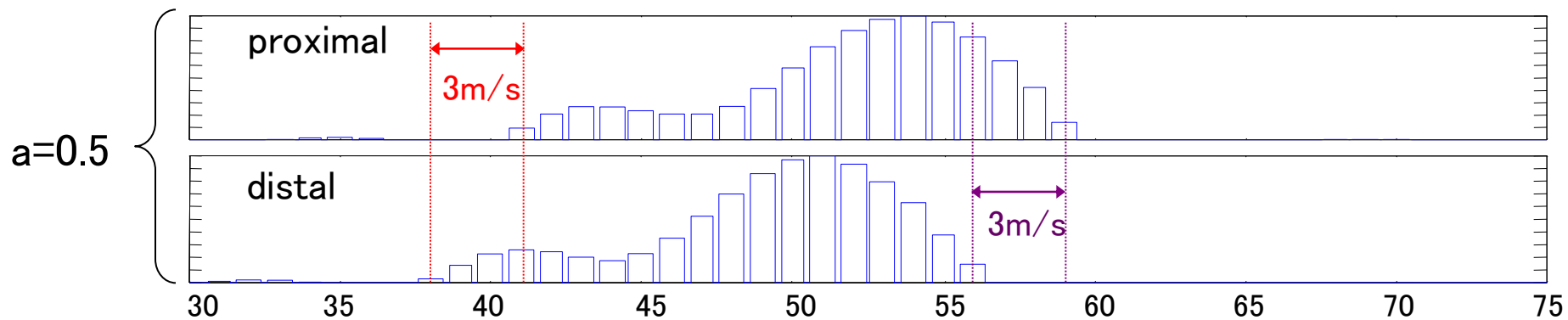
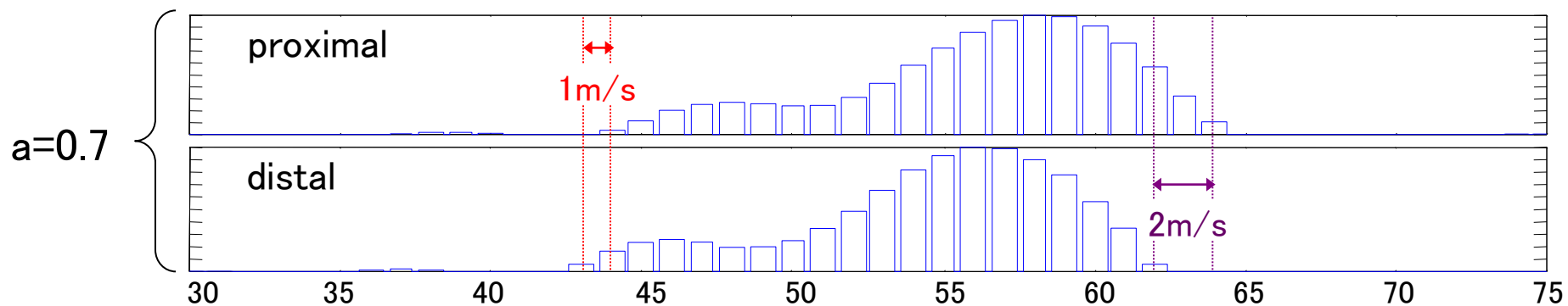
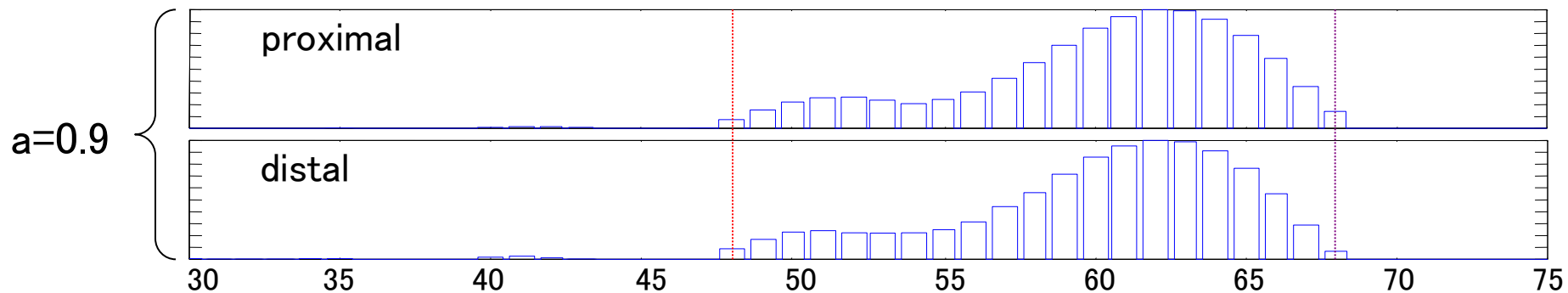
$V_{max}: 63\text{m/s}$
 $V_{min}: 36\text{m/s}$

DCV estimated from distal CAPs (below elbow)



$V_{max}: 71\text{m/s}$
 $V_{min}: 50\text{m/s}$





Inversion of the Causality

Thank you very much