

## Lab3: Event Related Potential Analysis

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## Submission Policy

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Read all the instructions below carefully before you start working on the assignment, and before you make a submission. For this assignment, please hand in the following your report (pdf) and code (.ipynb or .m file).

- **PLAGIARISM IS STRICTLY PROHIBITED. (0 point for Plagiarism)**
- For mathematical problem(s), please show your work step by step and clarify statement of theorem you use (if any). Answering without mathematical derivations will get 0 point.
- Submission deadline: **2021.05.04 09:00:00 AM.**
- **Late submission penalty formula:**

$$\text{original score} \times (0.7)^{\#(\text{days late})}$$

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## File Format

- Each group submits 1 report (.pdf and .tex file) and 1 code (.ipynb or .m).
- **Report** must contains observations, results and explanations. Please name your .pdf and .tex file as **5275\_Lab3\_GroupNum.pdf** and **5275\_Lab3\_GroupNum.tex**, respectively.
- Paper submission is not allowed. **Please use our L<sup>A</sup>T<sub>E</sub>X template to complete your report.**
- **Code** file must contains comments to explain your code. Please name your code file as **5275\_Lab3\_GroupNum.ipynb/.m**
- Implementation will be graded by completeness, algorithm correctness, model description, and discussion.
- **Illegal format penalty:** -5 points for violating each rule of file format.

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## Prerequisite

To finish programming problem, you could choose Matlab or Python base on your programming preference.

### Matlab 2020a+

- [NYCU installation page](#)
- [NCTU installation tutorial](#)
- [EEGLab official installation page](#) (v2020.0+ is recommended)

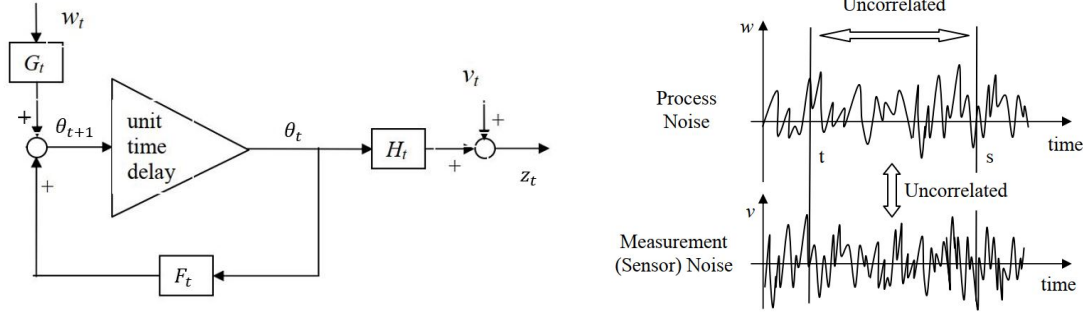
### Python 3.7+

- [MNE official installation page](#) (0.20.7+ is recommended)

# 1 Mathematical problem

## 1.1 Denoising the ERP signals–Kalman Filtering

### 1.1.1 Framework of Kalman filtering



**Figure: (Left) State space representation of linear time varying system (ERP) with process noise and measurement noise. (Right) Noise characteristics.**

#### Model Formalization

Let  $\theta_t \in \mathbb{R}^{k \times 1}$  denotes the input signal (state) and  $z_t \in \mathbb{R}^{M \times 1}$  denotes the output signal at time  $t$ . According to *S. D. Georgiadis et al.*, both  $\theta_t$  and  $z_t$  are defined as vector-valued processes. We could construct a state-space model for the linear dynamic systems (ERP) as below:

$$\theta_{t+1} = F_t \theta_t + G_t w_t, \quad z_t = H_t \theta_t + v_t \quad (1.1)$$

with initial condition  $\theta_0$ . Here we define  $w_t \in \mathbb{R}^{k \times 1}$  as the process noise with zero mean,  $v_t \in \mathbb{R}^{M \times 1}$  as the measurement noise with zero mean,  $F_t \in \mathbb{R}^{k \times k}$  as the transition matrix, and  $H_t \in \mathbb{R}^{M \times k}$ ,  $G_t \in \mathbb{R}^{k \times k}$ .

#### Hypothesis of ERP system

- $F_t$ ,  $G_t$ , and  $H_t$  are known sequences of matrices
- $(\theta_0, w_t, v_t)$  is a sequence of mutually uncorrelated random vectors with finite variance
- $E[w_t] = \mathbf{0}_{k \times 1}$ ,  $E[v_t] = \mathbf{0}_{M \times 1} \quad \forall t$
- The covariances  $C_w$ ,  $C_v$ , and  $C_{wv}$  are known sequences of matrices.

Given the following conditions:

$$C_v(t, s) = E[v_t \cdot v_s^T] = \begin{cases} \mathbf{0}_{M \times M}, & \text{where } t \neq s \\ R_{t, M \times M}, & \text{where } t = s \end{cases} \quad (1.2)$$

$$C_w(t, s) = E[w_t \cdot w_s^T] = \begin{cases} \mathbf{0}_{k \times k}, & \text{where } t \neq s \\ Q_{t, k \times k}, & \text{where } t = s \end{cases} \quad (1.3)$$

$$C_{wv}(t, s) = E[w_t \cdot v_s^T] = \mathbf{0}_{k \times M}, \quad \forall t, \forall s \quad (1.4)$$

To obtain an optimal value of  $\theta_t$  based on measurements  $z_t$ , we minimize the mean square error:

$$J_t = E[(\hat{\theta}_t - \theta_t)^T (\hat{\theta}_t - \theta_t)] \quad (1.5)$$

with the constraints (1.1) to (1.4). We call  $\hat{\theta}_{t|t-1}$  as expected state transition based on model,  $\hat{z}_t$  as expected output.

$$\begin{aligned} \theta_t &= F_{t-1} \theta_{t-1} + G_{t-1} w_{t-1} \\ \hat{\theta}_{t|t-1} &= E[F_{t-1} \hat{\theta}_{t-1} + G_{t-1} w_{t-1}] = F_{t-1} \hat{\theta}_{t-1} + G_{t-1} E[w_{t-1}] \\ \hat{z}_t &= E[H_t \hat{\theta}_{t|t-1} + v_t] = H_t \hat{\theta}_{t|t-1} + E[v_t] = H_t \hat{\theta}_{t|t-1} \end{aligned} \quad (1.6)$$

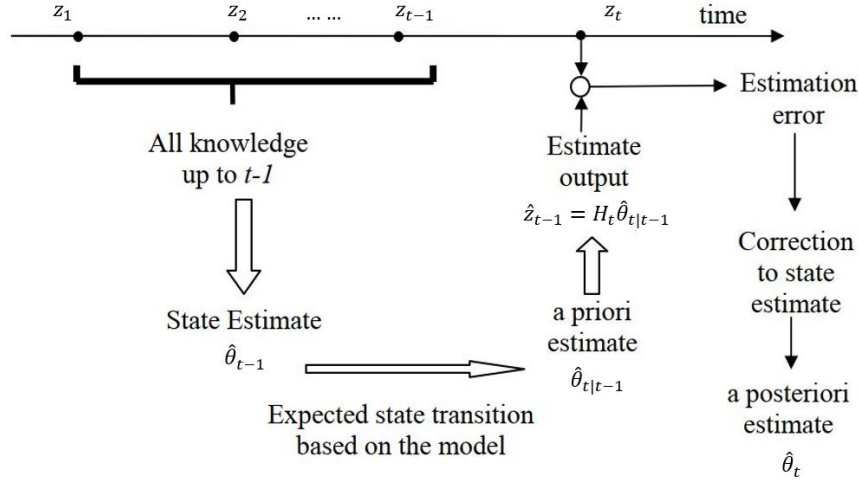


Figure: Outline of the Kalman filter algorithm

### 1.1.2 Correction of the state estimate

Assimilating the new measurement  $z_t$ , we can update the state estimate in proportion to the output estimation error.

$$\hat{\theta}_t = \hat{\theta}_{t|t-1} + K_t(z_t - \hat{z}_t) \quad (1.7)$$

Let  $\epsilon_t = \hat{\theta}_{t|t-1} - \theta_t$  be a priori estimation error, then

$$\begin{aligned} e_t &\equiv \hat{\theta}_t - \theta_t = \hat{\theta}_{t|t-1} + K_t(z_t - H_t \hat{\theta}_{t|t-1}) - \theta_t \\ &= \hat{\theta}_{t|t-1} + K_t(H_t \theta_t + v_t - H_t \hat{\theta}_{t|t-1}) - \theta_t = (\hat{\theta}_{t|t-1} - \theta_t) - K_t H_t (\hat{\theta}_{t|t-1} - \theta_t) + K_t v_t \\ &= (I_k - K_t H_t) \epsilon_t + K_t v_t \end{aligned} \quad (1.8)$$

Equation (1.7) provides a structure of linear filter in recursive form. Denoting  $K_t \in \mathbb{R}^{k \times M}$  as a gain matrix to be optimized so that the mean squared error (expectation of  $e_t^T e_t$ ) of state estimation may be minimized.

#### Problem 1

(5 points)

Please show that

$$e_t^T e_t = \epsilon_t^T \epsilon_t + \epsilon_t^T H_t^T K_t^T K_t H_t \epsilon_t - 2 \epsilon_t^T K_t H_t \epsilon_t + 2 \epsilon_t^T K_t^T v_t - 2 v_t^T K_t^T K_t H_t \epsilon_t + v_t^T K_t^T K_t v_t \quad (1.9)$$

#### Problem 1's answer

First, we calculate and rewrite  $e_t$  and  $e_t^T$

$$e_t = (I_k - K_t H_t) \epsilon_t + K_t v_t = \epsilon_t - K_t H_t \epsilon_t + K_t v_t$$

$$e_t^T = \epsilon_t^T (I_k - K_t H_t)^T + v_t^T K_t^T = \epsilon_t^T (I_k - H_t^T K_t^T) + v_t^T K_t^T = \epsilon_t^T - \epsilon_t^T H_t^T K_t^T + v_t^T K_t^T$$

$$\begin{aligned} e_t^T e_t &= \epsilon_t^T \epsilon_t - \epsilon_t^T K_t H_t \epsilon_t + \epsilon_t^T K_t v_t - \epsilon_t^T H_t^T K_t^T \epsilon_t + \epsilon_t^T H_t^T K_t^T K_t H_t \epsilon_t \\ &\quad - \epsilon_t^T H_t^T K_t^T K_t v_t + v_t^T K_t^T \epsilon_t - v_t^T K_t^T K_t H_t \epsilon_t + v_t^T K_t^T K_t v_t \quad \text{-- eq(1)} \end{aligned}$$

We know that  $(\epsilon_t^T K_t H_t \epsilon_t)^T = \epsilon_t^T H_t^T K_t^T \epsilon_t$  and  $(\epsilon_t^T K_t v_t)^T = v_t^T K_t^T \epsilon_t$

and  $(v_t^T K_t^T K_t H_t \epsilon_t)^T = \epsilon_t^T H_t^T K_t^T K_t v_t$  and all of them are const

Hence, we can rewrite eq(1) to

$$e_t^T e_t = \epsilon_t^T \epsilon_t + \epsilon_t^T H_t^T K_t^T K_t H_t \epsilon_t - 2 \epsilon_t^T K_t H_t \epsilon_t + 2 \epsilon_t^T K_t v_t - 2 v_t^T K_t^T K_t H_t \epsilon_t + v_t^T K_t^T K_t v_t$$

Let us differentiate the scalar function  $e_t^T e_t$  with respect to matrix  $K_t$  by using the following matrix differentiation rules.

**Matrix differentiation rule 1**

Let  $a \in \mathbb{R}^{k \times 1}$ ,  $b \in \mathbb{R}^{M \times 1}$ , and  $K \in \mathbb{R}^{k \times M}$  is same as above  $K_t$  (We omit the subscript  $t$  for brevity).

$$f \equiv [a_1, \dots, a_k] \begin{bmatrix} K_{11} & \dots & K_{1M} \\ \vdots & \ddots & \vdots \\ K_{k1} & \dots & K_{kM} \end{bmatrix} \begin{bmatrix} b_1 \\ \vdots \\ b_M \end{bmatrix} = a^T K b \Rightarrow \frac{df}{dK} = \left[ \frac{\partial f}{\partial K_{ij}} \right] = [a_i b_j] = ab^T, \quad \forall i \in \mathbb{Z}_k, j \in \mathbb{Z}_M \quad (1.10)$$

**Matrix differentiation rule 2**

Let  $b, c \in \mathbb{R}^{M \times 1}$ , and  $K \in \mathbb{R}^{k \times M}$ , and  $g = c^T K^T K b$ , then

$$\frac{dg}{dK_t} = \left[ \frac{\partial g}{\partial K_{im}} \sum_{i=1}^M \sum_{j=1}^k \sum_{l=1}^k K_{il} c_l K_{ij} b_j \right] = \left[ \sum_{j=1}^k c_m K_{ij} b_j + \sum_{j=1}^k K_{il} c_l b_m \right] = K b c^T + K c b^T \quad (1.11)$$

**Problem 2**

(15 points)

Use the matrix differentiation rule 1 and 2 to show that

$$\frac{de_t^T e_t}{dK_t} = 2K_t H_t \epsilon_t \epsilon_t^T H_t^T - 2[K_t H_t \epsilon_t v_t^T + K_t v_t \epsilon_t^T H_t^T] + 2K_t v_t v_t^T + 2[\epsilon_t v_t^T - \epsilon_t \epsilon_t^T H_t^T] \quad (1.12)$$

Problem 2's answer

We get 2 matrix difference rules from previous block:

rule 1:  $\frac{d}{dK} (a^T K b) = ab^T$

rule 2:  $\frac{d}{dK} (a^T K^T K b) = K b a^T + K a b^T$

$$\frac{de_t^T e_t}{dK_t} = \frac{d}{dK_t} (\epsilon_t^T \epsilon_t + \epsilon_t^T H_t^T K_t^T K_t H_t \epsilon_t - 2\epsilon_t^T K_t H_t \epsilon_t + 2\epsilon_t^T K_t v_t - 2v_t^T K_t^T K_t H_t \epsilon_t + v_t^T K_t^T K_t v_t)$$

$$= \frac{d}{dK_t} (\epsilon_t^T H_t^T K_t^T K_t H_t \epsilon_t) + \frac{d}{dK_t} (-2\epsilon_t^T K_t H_t \epsilon_t + 2\epsilon_t^T K_t v_t - 2v_t^T K_t^T K_t H_t \epsilon_t + v_t^T K_t^T K_t v_t)$$

Set  $a = b = H_t \epsilon_t$  in red part of above equation, then we can get a new equation by rule2:

$$\frac{de_t^T e_t}{dK_t} = 2K_t H_t \epsilon_t \epsilon_t^T H_t^T - 2 \frac{d}{dK_t} (\epsilon_t^T K_t H_t \epsilon_t) + \frac{d}{dK_t} (2\epsilon_t^T K_t v_t - 2v_t^T K_t^T K_t H_t \epsilon_t + v_t^T K_t^T K_t v_t)$$

Set  $a = \epsilon_t, b = H_t \epsilon_t$  in red part of above equation, then we can get a new equation by rule1:

$$\frac{de_t^T e_t}{dK_t} = 2K_t H_t \epsilon_t \epsilon_t^T H_t^T - 2\epsilon_t \epsilon_t^T H_t^T + 2 \frac{d}{dK_t} (\epsilon_t^T K_t v_t) + \frac{d}{dK_t} (-2v_t^T K_t^T K_t H_t \epsilon_t + v_t^T K_t^T K_t v_t)$$

Set  $a = \epsilon_t, b = v_t$  in red part of above equation, then we can get a new equation by rule1:

$$\frac{de_t^T e_t}{dK_t} = 2K_t H_t \epsilon_t \epsilon_t^T H_t^T - 2\epsilon_t \epsilon_t^T H_t^T + 2\epsilon_t v_t^T + \frac{d}{dK_t} (-2v_t^T K_t^T K_t H_t \epsilon_t + v_t^T K_t^T K_t v_t)$$

$$= 2K_t H_t \epsilon_t \epsilon_t^T H_t^T + 2(\epsilon_t v_t^T - \epsilon_t \epsilon_t^T H_t^T) - 2 \frac{d}{dK_t} (v_t^T K_t^T K_t H_t \epsilon_t) + \frac{d}{dK_t} (v_t^T K_t^T K_t v_t)$$

Set  $a = v_t, b = H_t \epsilon_t$  in red part of above equation, then we can get a new equation by rule2:

$$\frac{de_t^T e_t}{dK_t} = 2K_t H_t \epsilon_t \epsilon_t^T H_t^T + 2(\epsilon_t v_t^T - \epsilon_t \epsilon_t^T H_t^T) - 2(K_t H_t \epsilon_t v_t^T + K_t v_t \epsilon_t^T H_t^T) + \frac{d}{dK_t} (v_t^T K_t^T K_t v_t)$$

Set  $a = b = v_t \epsilon_t$  in red part of above equation, then we can get a new equation by rule2:

$$\frac{de_t^T e_t}{dK_t} = 2K_t H_t \epsilon_t \epsilon_t^T H_t^T - 2(K_t H_t \epsilon_t v_t^T + K_t v_t \epsilon_t^T H_t^T) + 2K_t v_t v_t^T + 2(\epsilon_t v_t^T - \epsilon_t \epsilon_t^T H_t^T)$$

The necessary condition for the mean squared error of state estimate with respect to the gain matrix  $K_t$  is:

$$\frac{dJ_t}{dK} = \mathbf{0}_{k \times M}$$

Taking expectation of  $e_t^T e_t$ , differentiating it w.r.t.  $K_t$  and setting it to zero yield:

$$E[K_t H_t \epsilon_t \epsilon_t^T H_t^T - K_t H_t \epsilon_t v_t^T - K_t v_t \epsilon_t^T H_t^T + K_t v_t v_t^T + \epsilon_t v_t^T - \epsilon_t \epsilon_t^T H_t^T] = \mathbf{0}_{k \times M} \quad (1.13)$$

Which means that  $K_t$  and  $H_t$  can be factored out,

$$K_t H_t E[\epsilon_t \epsilon_t^T] H_t^T - K_t H_t E[\epsilon_t v_t^T] - K_t E[v_t \epsilon_t^T] H_t^T + K_t E[v_t v_t^T] + E[\epsilon_t v_t^T] - E[\epsilon_t \epsilon_t^T] H_t^T = \mathbf{0}_{k \times M} \quad (1.14)$$

Since we know that

$$\hat{\theta}_{t|t-1} = E[F_{t-1}\hat{\theta}_{t-1} + G_{t-1}w_{t-1}] = F_{t-1}\hat{\theta}_{t-1} \quad (1.15)$$

and

$$\epsilon_t = \hat{\theta}_{t|t-1} - \theta_t,$$

we can examine  $E[\epsilon_t v_t^T] = E[(\hat{\theta}_{t|t-1} - \theta_t)v_t^T] = E[(\hat{\theta}_{t|t-1}v_t^T] - E[\theta_t v_t^T] = \mathbf{0}_{k \times M}$

### Problem 3

(10 points)

Please show that

$$E[\epsilon_t v_t^T] = \mathbf{0}_{k \times M} \text{ \& } E[v_t \epsilon_t^T] = \mathbf{0}_{M \times k} \quad (1.16)$$

Let us define the error covariance of a priori state estimation

$$C_{\hat{\theta}_{t|t-1}} \equiv E[\epsilon_t \epsilon_t^T] = E[(\hat{\theta}_{t|t-1} - \theta_t)(\hat{\theta}_{t|t-1} - \theta_t)^T] \quad (1.17)$$

### Problem 4

(5 points)

Please show that

$$K_t = C_{\hat{\theta}_{t|t-1}} H_t^T \left( H_t C_{\hat{\theta}_{t|t-1}} H_t^T + C_v(t, t) \right)^{-1} \quad (1.18)$$

Such  $K_t$  is called the **Kalman Gain**.

### 1.1.3 Updating the Error Covariance

The above Kalman gain contains the a priori error covariance  $C_{\hat{\theta}_{t|t-1}}$ . This must be updated recursively based on each new measurement and the state transition model. Define the a posteriori state estimation error covariance

$$C_{\hat{\theta}_t} = E[e_t e_t^T] = E[(\hat{\theta}_t - \theta_t)(\hat{\theta}_t - \theta_t)^T] \quad (1.19)$$

### Problem 5

(5 points)

Please show that

$$C_{\hat{\theta}_t} = (I_k - K_t H_t) C_{\hat{\theta}_{t|t-1}} \quad (1.20)$$

Derive (1.21), one can compute  $C_{\hat{\theta}_{t+1|t}}$  by using the state transition equation (1.1).

Consider

$$\epsilon_{t+1} = \hat{\theta}_{t+1|t} - \theta_{t+1|t} = F_t \hat{\theta}_t - (F_t \theta_t + G_t w_t) = F_t e_t - G_t w_t. \quad (1.21)$$

From (1.17)

$$\begin{aligned} C_{\hat{\theta}_{t+1|t}} &= E[\epsilon_{t+1} \epsilon_{t+1}^T] \\ &= E[(F_t \theta_t + G_t w_t)(F_t \theta_t + G_t w_t)^T] \\ &= F_t E[e_t e_t^T] F_t^T - G_t E[w_t e_t^T] F_t^T - F_t E[e_t w_t^T] G_t^T + G_t E[w_t w_t^T] G_t^T \end{aligned} \quad (1.22)$$

### Problem 6

(5 points)

Please show that

$$C_{\hat{\theta}_{t|t-1}} = F_{t-1} C_{\hat{\theta}_{t-1}} F_{t-1}^T + G_{t-1} C_w(t-1, t-1) G_{t-1}^T \quad (1.23)$$

## 1.1.4 The Recursive Calculation Procedure for the Discrete Kalman Filter

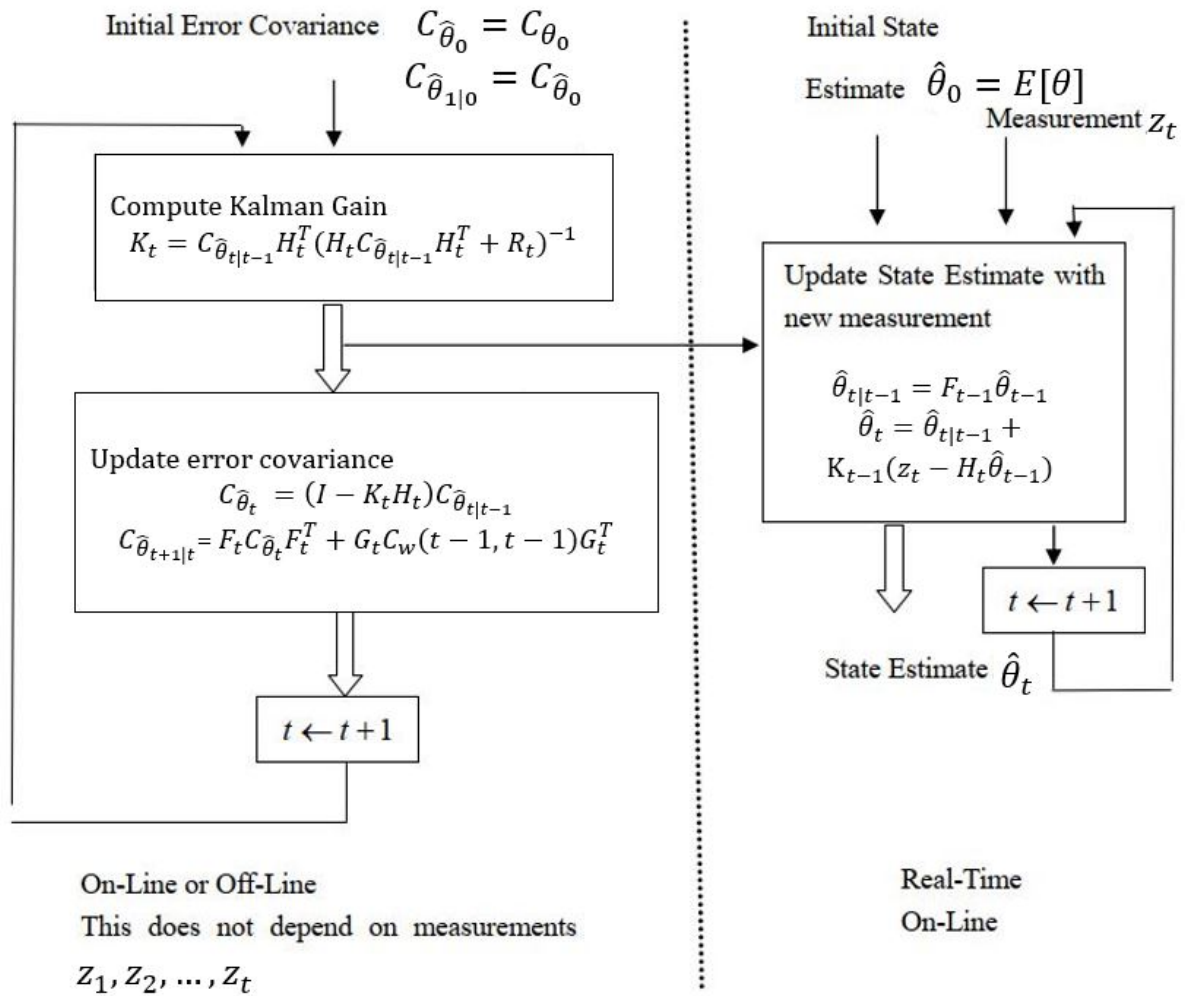


Figure: Solve discrete Kalman Filter recursively

## 2 Multiple choices

Please give a brief explanation for option(s) you choose. Answering without any description will get 0 point.

### Problem 7

(5 points)

Which of the following statements are true regarding baseline correction? Assume that we are using **stimulus-locked epochs**.

- (A) To perform baseline correction, the mean voltage is calculated during the prestimulus portion of the epoch, and this value is then subtracted from every point in the prestimulus period.
- (B) To perform baseline correction, the mean voltage is calculated during the prestimulus portion of the epoch, and this value is then subtracted from every point in the waveform.
- (C) We take the mean of the prestimulus period (rather than just taking the voltage at time zero) so that we can average out random noise during the prestimulus period and obtain a better estimate of the voltage offset.
- (D) We take the mean of the prestimulus period (rather than just taking the voltage at time zero) so that we can obtain a better estimate of the noise level.

### Problem 8: Single choice

(5 points)

Imagine that a researcher conducts a study comparing a patient group with a control group in an oddball paradigm. The researcher conducts a separate patient/control  $x$  rare/frequent ANOVA for each time point from 0-800 ms at each electrode site. Each ANOVA yielded 3  $p$  values (main effect of patient/control, main effect of rare/frequent, and interaction). The sampling rate was 250 Hz, so there were 200 time points between 0 and 800 ms. There were 32 electrode sites. If there are no true differences between groups, how many significant  $p$  values would you expect the researcher to obtain as a result of noise in the data? [For simplicity, assume that every time point and electrode site is independent of every other time point and electrode site. Assume that  $\alpha = 0.05$ .]

- (A) 1280 (B) 507 (C) 320 (D) 960

### Problem 9

(5 points)

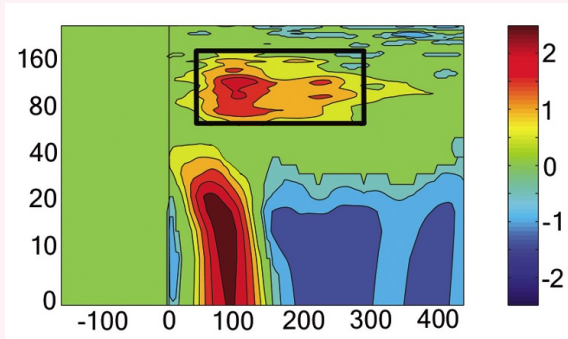
Imagine that a researcher conducts a go/no-go experiment in which subjects are supposed to press a button every time they see the word GO (written in green, 80% of trials) and to make no response when they see the word STOP (written in red, 20% of trials). And imagine that they find a larger N1 wave (at 170 ms) for the STOP stimulus than for the GO stimulus. Could this effect be plausibly explained by a physical stimulus confound?

- (A) No. It is unlikely that the small physical differences between GO and STOP could explain a difference at 170 ms.
- (B) Yes, because subjects may have been looking at a different places on the screen when the words GO and STOP appeared, which would change the position of the stimulus on the retina.
- (C) Yes, because the word STOP contains more letters than the word GO and therefore might elicit a larger N1.
- (D) Yes, because it is possible that red stimuli elicit a larger N1 than green stimuli.

**Problem 10**

(5 points)

The time-frequency plot below shows data from the oddballs in a mismatch negativity paradigm. Which of the following statements are true about this plot?



- (A) The X axis is time.
- (B) The Y axis is a measure of magnitude (typically amplitude or power).
- (C) If we wanted to reproduce the original data from a set of wavelets, we would need some high-amplitude wavelets centered at 100 ms with frequencies ranging from 0 to 20 Hz (in addition to wavelets at other frequencies).
- (D) The activity shown in the box from 80-280 milliseconds is probably a genuine oscillation.



### 3 Coding problem

**Problem 11: Auditory Oddball paradigm**

(2+2+2+2+2+2+2=16 points)

Please use the data: Day1\_ERP.set to answer these questions.

**Data Information**

This data contains 2 sessions, been down-sampled to 250Hz, and been band-pass filtered.

Trigger	Event
10	Response
2	High pitch
3	Low pitch
4	End of session

- (a) Please guess the range of band-pass filtered and show how you find this range.
- (b) Please guess the portion of High Pitch: Low pitch and show how you find it.
- (c) Plot the Fz, Cz, and Pz's average ERP for Response respectively.
- (d) Plot the Fz, Cz, and Pz's average ERP for High pitch and Low pitch respectively.

**For subproblem (e) and (f), please plot topolots for P300.**

Suppose that for each channel, P300 occurs during  $[300, 400]msec$  when  $t = 0$  indicates onset time of High pitch and Low pitch. That is,  $P300^{ch} \in \mathbb{R}^{51 \times 1} \forall ch \in \mathbb{Z}_{30}$ .

- (e) Plot topoplot for High pitch and Low pitch respectively. (Use  $mean(P300^{ch}) \forall ch \in \mathbb{Z}_{30}$ )
- $\forall ch \in \mathbb{Z}_{30}$ , define Min-Max normalization as below

$$\frac{mean(P300^{ch}) - \min \{ mean(P300^{ch}) | ch \in \mathbb{Z}_{30} \}}{\max \{ mean(P300^{ch}) | ch \in \mathbb{Z}_{30} \} - \min \{ mean(P300^{ch}) | ch \in \mathbb{Z}_{30} \}} \quad (3.1)$$

- (f) Plot topoplot for High pitch and Low pitch respectively with Min-Max normalization.
- If we define signal-to-noise ratio (SNR) for each channel as below:

$$SNR^{ch} = \frac{P300^{ch}}{std(Baseline^{ch})} \quad (3.2)$$

where baseline interval  $[-200, 0]msec$ ,  $Baseline^{ch}$  is mean by trial, and  $t = 0$  indicates onset time of High pitch and Low pitch.

- (g) For each channel, plot SNR for High pitch and Low pitch. (Bar plot)
- (h) Plot cumulative (by trial) SNR for Fz, Cz, and Pz channel and give a description of your observation.

**Problem 12: 5 target SSVEP paradigm**

(4+8+7=19 points)

Please use the data: Day 2\_SSVEP.set to answer these questions.

**Data Information**

Trigger	Event
11	10 Hz
21	11 Hz
31	12 Hz
41	13 Hz
51	Nan

(a) For Fz and Oz, please plot average ERP for each type of stimuli.

**Apply short time Fourier transform ([spectrogram in matlab](#)) with the following parameters to answer subproblem (b).**

% B: SSVEP for certain channel, sfreq:sampling rate

% P is a power spectrum density matrix with size (N\_freq, N\_time)

[S,F,T,P]=spectrogram(B,sfreq,sfreq/2,sfreq,sfreq);

(b) Plot power v.s. frequency for each stimuli at  $F_z$  and  $O_z$  channel and give description of your observation.**We extract {10,11,12,13}Hz from PSD you get from subproblem (b), and called it as response frequency.**(c) Plot topolot of response Hz v.s. stimuli Hz with same Min-Max normalization technique. That is, you will plot  $4 \times 5 = 20$  topoplots this time.**References**

- [1] Stefanos D. Georgiadis, Perttu O. Ranta-aho, Mika P. Tarvainen, Pasi A. Karjalainen, *Single-Trial Dynamical Estimation of Event-Related Potentials: A Kalman Filter-Based Approach*, IEEE Transactions on Biomedical Engineering, 52(8), 2005.
- [2] Harry Asada, Lecture notes for *Identification, Estimation, and Learning*, Massachusetts Institute of Technology, Department of Mechanical Engineering, 2006.
- [3] S. Sanei, J.A. Chambers, *EEG Signal Processing*, Wiley, 2007.
- [4] Yuan-Pin Lin, Lecture notes for *3<sup>rd</sup> EEG summer workshop*, National Sun Yat-sen University, Institute of Medical Science and Technology, 2020.
- [5] Mike X Cohen. *Analyzing neural time series data : theory and practice*. Cambridge, Massachusetts :The MIT Press, 2014.
- [6] Donald L. Schomer and Fernando H. Lopes da Silva, *Niedermeyer's Electroencephalography: Basic Principles, Clinical Applications, and Related Fields*, Lippincott William & Wilkins, 2011. ISBN 9780781789424.

## 4 Feedback for Lab 3

This part is not for grading but for understanding learning situation of each student. Please give us your feedback and comments.

### 4.1 Work Division

For example,

Student ID	Name	Be response for... ..
123456789	Tony	solving Problem 1 and designing preprocessing algorithm in problem 7
987654321	May	solving Problem 3 and designing preprocessing algorithm in problem 7

### 4.2 Suggestions and Comments

#### 4.2.1 For instructor

#### 4.2.2 For teaching assistant(s)

##### 4.2.2.a For Min-Jiun

##### 4.2.2.b For Eric

### Office Hour Information

We'll have limited time to teach EEGLab and MNE on our course; therefore, if you have any question about lab 2, feel free to make an appointment or come to ask me during my office hour.

Day	Time	Office
Tue.	12:20 p.m.-13:10 p.m.	EC120
Thur.	06:30 p.m.-09:30 p.m.	SC207

#### Note

Actually, my office hour on Thursdays is main for calculus consultation. If there are undergraduate students come to ask calculus problems, I need to teach them first and then to solve your problem during the rest of the office hour on Thursday nights.