

# Mathematical Model of Input for Peak-Detector

You

May 20, 2016

## 1 Introduction

For the “freq\_timing\_est” block, frequency and timing information are supposed to be estimated. As discussed in the “freq\_timing\_tradeoff”, we can use brutal search to get the correct value. But, before we make our decision by choosing the maximum peak, we still need to have a rigorous mathematic model for the peak.

This article will discuss this problem step to step.

## 2 Mathematical Model

Because the signal we received are discrete values, so we only consider about discrete signals, rather than continuous ones.

Notation	Description
$s_k$	received sample at time $k$
$t_k$	training sample at time $k$
$d_k$	data sample at time $k$
$n_k$	noise at time $k$
$P_k^t$	the $k^{th}$ chip of spread code for one frame of training
$P_k^d$	the $k^{th}$ chip of spread code for one frame of data
$D_l^t$	the $l^{th}$ symbol for training
$D_l^d$	the $l^{th}$ symbol for data
$N_f$	number of chips per frame
$N_c$	number of chips per symbol
$N_s$	number of symbols per frame
$N_{s'}$	number of symbols per shortened training sequence
$\sigma^2$	variance of Gaussian noise
$k_0$	number of samples of delay
$f_0$	frequency offset
$T_c$	duration between two chips

Table 1: Notation Table

First, the structure of training and data frame are like: The structure of training is like Fig. 1 and Fig. 2

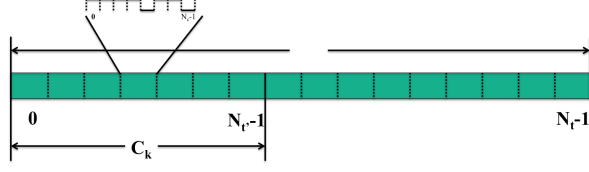


Figure 1: Training Frame Structure

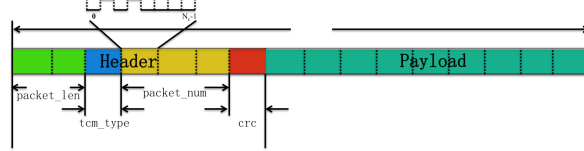


Figure 2: Data Frame Structure

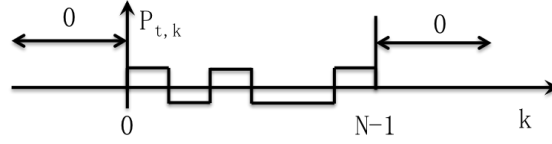


Figure 3: Sketch Map of  $P_k^t$

## 2.1 Description of Variables

We first express each variables by mathematical languages.

According to the description in table 1, and also in order to simplify the following notation, the definition of  $P_y^x$  is defined as

$$P_k^x = \begin{cases} P_k^x & k = 0, \dots, N_c - 1 \\ 0 & \text{else} \end{cases} \quad (1)$$

$x = \text{"t" or "d"}$

For instance, the figure for  $P_k^t$  is like Fig. 3

So, training chip at time  $k$  can be described as:

$$t_k = \sum_{k=0}^{N_c} D_0^t P_k^t \quad (2)$$

$$= D_0^t P_k^t \quad (3)$$

If we consider the frame-level periodicity,  $t_k$  would be

$$t_k = D_{[k/N_c] \% N_s}^t P_{k \% N_c}^t \quad (4)$$

Based on nearly the same idea,  $d_k$  can be written as:

$$d_k = D_{[k/N_c]}^d P_{k \% N_c}^d \quad (5)$$

Noise is simple. We simply choose IID Gaussian noise. So

$$n_k \sim \mathcal{N}(0, \sigma^2) \quad (6)$$

## 2.2 Description of Output of Matched Filter

Consider the time delay and frequency offset, the received signal would be

$$r_k = (t_{k-k_0} + d_{k-k_0})e^{j2\pi f_0 k T_c} + n_k \quad (7)$$

We first deal with the contribution of noise. Define the Pulse Response of Matched Filter to be  $h_{N_f-k}$ .

$$h_k = \begin{cases} P_k^t = D_{\lfloor k/N_c \rfloor}^t P_{k \% N_c}^t & k = 0, \dots, N_f \\ 0 & \text{else} \end{cases} \quad (8)$$

Let  $g_{k_0}^n = \sum_{k'=0}^{N_f-1} n_{k'} \cdot h_{k'}$

$$\mathbb{E}\{g_{k_0}^n\} = \mathbb{E}\left\{\sum_{k'=0}^{N_f-1} n_{k'} \cdot h_{k'}\right\} \quad (9)$$

$$= \sum_{k'=0}^{N_f-1} \mathbb{E}\{n_{k'} \cdot h_{k'}\} \quad (10)$$

$$= \sum_{k'=0}^{N_f-1} \mathbb{E}\{n_{k'}\} h_{k'} \quad (11)$$

$$= \sum_{k'=0}^{N_f-1} 0 \cdot h_{k'} \quad (12)$$

$$= 0 \quad (13)$$

$$\mathbb{E}\{(g_{k_0}^n)^2\} = \mathbb{E}\left\{\sum_{k'=0}^{N_f-1} (n_{k'} \cdot h_{k'})\right\} \quad (14)$$

$$= \mathbb{E}\left\{\sum_{k'=0}^{N_f-1} n_{k'}^2 \cdot \underbrace{(h_{k'})^2}_{\equiv 1}\right\} \quad (15)$$

$$= \sum_{k'=0}^{N_f-1} \mathbb{E}\{n_{k'}^2\} \quad (16)$$

$$= N_f \sigma^2 \quad (17)$$

So  $g_{k_0}^n \sim \mathcal{N}(0, N_f \sigma^2)$

The next step is to analyze the output of Matched Filter. Define the pattern for Matched Filter for training frame to be  $P_{-k}^{t*}$ . The output of the Matched

Filter at sampled point  $k = N_f$  is:

$$g_{k_0} = r_k * h_{N_f-k} \Big|_{k=N_f-1} \quad (18)$$

$$= (t_{k-k_0} + d_{k-k_0} + n_k) * h_{N_f-1-k} \Big|_{k=N_f-1} \quad (19)$$

$$= \underbrace{\sum_{k'=0}^{N_f-1} t_{k'-k_0} \cdot h_{k'}}_{g_{k_0}^t} + \underbrace{\sum_{k'=0}^{N_f-1} d_{k'-k_0} \cdot h_{k'}}_{g_{k_0}^d} + \underbrace{\sum_{k'=0}^{N_f-1} n_{k'} \cdot h_{k'}}_{g_{k_0}^n} \quad (20)$$

$$= g_{k_0}^t + g_{k_0}^d + g_{k_0}^n \quad (21)$$

Now, we will discuss all the possible situations for timing. Let's formate the time offset  $k_0$  in terms of  $N_s$  and  $N_c$ .

$$k_0 = \alpha \cdot N_c + \beta \quad \alpha = \mathbb{Z} \text{ and } \beta = 0, \dots, N_c - 1 \quad (22)$$

### 2.2.1 Perfectly Aligned

Perfectly Aligned means the sample at time  $k$  is also the first sample of patten for Matched Filter, as shown in fig. 4. For this situation,  $k_0$  satisfies

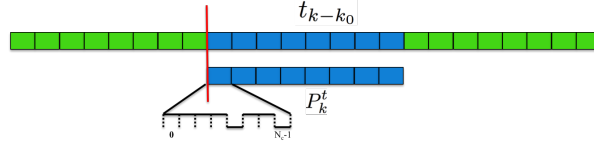


Figure 4: Perfectly Aligned

$$\begin{cases} \alpha = z \cdot N_s \quad z \in \mathbb{Z} \\ \beta = 0 \end{cases} \Rightarrow k_0 = z \cdot N_s \cdot N_c \quad (23)$$

Then we can analyze  $g_{k_0}^t$  and  $g_{k_0}^d$  separately

$$g_{k_0}^t = \sum_{k'=0}^{N_f-1} t_{k'-k_0} \cdot h_{k'} \quad (24)$$

$$= \sum_{k'=0}^{N_f-1} D_{[(k'-k_0)/N_c] \% N_s}^t P_{k' \% N_c}^t \cdot h_{k'} \quad (25)$$

$$= \sum_{k'=0}^{N_f-1} D_{[(k'-z \cdot N_s \cdot N_c)/N_c] \% N_s}^t P_{k' \% N_c}^t \cdot h_{k'} \quad (26)$$

$$= \sum_{k'=0}^{N_f-1} D_{[k'/N_c] \% N_s}^t P_{k' \% N_c}^t \cdot h_{k'} \quad (27)$$

$$(28)$$

$$\therefore h_{k'} = D_{\lfloor k'/N_c \rfloor}^t P_{k' \% N_c}^t \quad (29)$$

$$\therefore g_{k_0}^t = \sum_{k'=0}^{N_f-1} D_{\lfloor k'/N_c \rfloor \% N_s}^t P_{k' \% N_c}^t \cdot D_{\lfloor k'/N_c \rfloor}^t P_{k' \% N_c}^t \quad (30)$$

$$= \sum_{k'=0}^{N_f-1} \underbrace{(D_{\lfloor k'/N_c \rfloor \% N_s}^t)^2}_{\equiv 1} \underbrace{(P_{k' \% N_c}^t)^2}_{\equiv 1} \quad (31)$$

$$= N_f \quad (32)$$

To analyze  $g_k^s$ , we will first define a function to describe the convolution

$$C_s^m(f_1, f_2, k_0) = \sum_{k=s}^{s+n} f_1(k) \cdot f_2(k - k_0) \quad (33)$$

The diagram of the above formula is like Fig.5

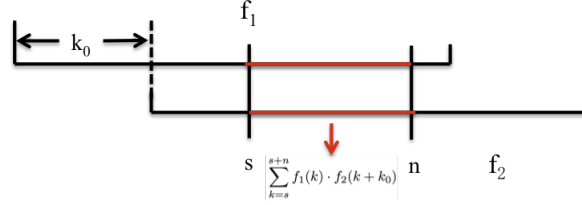


Figure 5: New Defined Convolution

$$g_{k_0}^d = \sum_{k'=0}^{N_f-1} d_{k'-k_0} \cdot h_{k'} \quad (34)$$

$$= \sum_{k'=0}^{N_f-1} D_{\lfloor (k'-k_0)/N_c \rfloor}^d P_{(k'-k_0) \% N_c}^d \cdot h_{k'} \quad (35)$$

$$= \sum_{k'=0}^{N_f-1} D_{\lfloor (k'-z \cdot N_s \cdot N_c)/N_c \rfloor}^d P_{(k'-z \cdot N_s \cdot N_c) \% N_c}^d \cdot h_{k'} \quad (36)$$

$$= \sum_{k'=0}^{N_f-1} D_{\lfloor k'/N_c \rfloor - z \cdot N_s}^d P_{k' \% N_c}^d \cdot D_{\lfloor k'/N_c \rfloor}^t P_{k' \% N_c}^t \quad (37)$$

$$(38)$$

For data symbols, we could only assume that

$$D_k^d = \begin{cases} +1 & p = 0.5 \\ -1 & p = 0.5 \end{cases} \quad (39)$$

Because the  $D_k^d$  here is a random variable, we could only exam the mean and variance for it, so do the  $g_{k_0}^d$

$$\mathbb{E}\{D_k^d\} = 1 \times 0.5 + (-1) \times 0.5 = 0 \quad (40)$$

$$\mathbb{E}\{(D_k^d)^2\} = 1 \times 0.5 + (-1)^2 \times 0.5 = 1 \quad (41)$$

and they are IID.

For  $g_{k_0}^d$ ,

$$\mathbb{E}\{g_{k_0}^d\} = \mathbb{E}\left\{\sum_{k'=0}^{N_f-1} D_{\lfloor k'/N_c \rfloor - z \cdot N_s}^d P_{k' \% N_c}^d \cdot D_{\lfloor k'/N_c \rfloor}^t P_{k' \% N_c}^t\right\} \quad (42)$$

$$= \sum_{k'=0}^{N_f-1} \mathbb{E}\{D_{\lfloor k'/N_c \rfloor - z \cdot N_s}^d P_{k' \% N_c}^d \cdot D_{\lfloor k'/N_c \rfloor}^t P_{k' \% N_c}^t\} \quad (43)$$

$$= \sum_{k'=0}^{N_f-1} P_{k' \% N_c}^d P_{k' \% N_c}^t \mathbb{E}\{D_{\lfloor k'/N_c \rfloor - z \cdot N_s}^d D_{\lfloor k'/N_c \rfloor}^t\} \quad (44)$$

$$= C_0^{N_c-1}(P_k^d, P_k^t, 0) \sum_{k''=\lfloor k'/N_c \rfloor}^{\lfloor k'/N_c \rfloor + N_s - 1} D_{k''}^t \mathbb{E}\{D_{k''-z}^d\} \quad (45)$$

$$= 0 \quad (46)$$

$$\mathbb{E}\{(g_{k_0}^d)^2\} = \mathbb{E}\left\{\sum_{k'=0}^{N_f-1} D_{\lfloor k'/N_c \rfloor - z \cdot N_s}^d P_{k' \% N_c}^d \cdot D_{\lfloor k'/N_c \rfloor}^t P_{k' \% N_c}^t\right\}^2 \quad (47)$$

$$= \mathbb{E}\left\{\sum_{k''=\lfloor k'/N_c \rfloor}^{\lfloor k'/N_c \rfloor + N_s - 1} D_{k''}^t D_{k''-z}^d \cdot \sum_{m=0}^{N_c} P_{m \% N_c}^d P_{m \% N_c}^t\right\}^2 \quad (48)$$

$$= \left(\sum_{m=0}^{N_c} P_m^d P_m^t\right)^2 \mathbb{E}\left\{\sum_{k''=\lfloor k'/N_c \rfloor}^{\lfloor k'/N_c \rfloor + N_s - 1} D_{k''}^t D_{k''-z}^d\right\}^2 \quad (49)$$

$$= (C_0^{N_c-1}(P_k^d, P_k^t, 0))^2 \mathbb{E}\left\{\sum_{k''=\lfloor k'/N_c \rfloor}^{\lfloor k'/N_c \rfloor + N_s - 1} D_{k''}^t D_{k''}^d\right\}^2 \quad (50)$$

$$= (C_0^{N_c-1}(P_k^d, P_k^t, 0))^2 \left(\mathbb{E}\left\{\sum_{m=\lfloor k'/N_c \rfloor}^{\lfloor k'/N_c \rfloor + N_s - 1} (D_m^t D_m^d)^2\right\}\right. \quad (51)$$

$$+ \mathbb{E}\left\{\sum_{m=\lfloor k'/N_c \rfloor}^{\lfloor k'/N_c \rfloor + N_s - 1} \sum_{n \neq m} D_m^t D_m^d D_n^t D_n^d\right\}\Bigg) \quad (52)$$

$$= (C_0^{N_c-1}(P_k^d, P_k^t, 0))^2 \left(\sum_{m=\lfloor k'/N_c \rfloor}^{\lfloor k'/N_c \rfloor + N_s - 1} \mathbb{E}\{D_m^d\}^2\right. \quad (53)$$

$$+ \sum_{m=\lfloor k'/N_c \rfloor}^{\lfloor k'/N_c \rfloor + N_s - 1} \sum_{n \neq m} D_m^t D_n^t \mathbb{E}\{D_m^d\} \mathbb{E}\{D_n^d\}\Bigg) \quad (54)$$

### 2.2.2 Chip-level Aligned

Chip-level Aligned means the start chip of received symbol is aligned with patten's symbol's first chip. But, the beginning symbol of a frame for received data may not be aligned with patten's first symbol. Here is the diagram

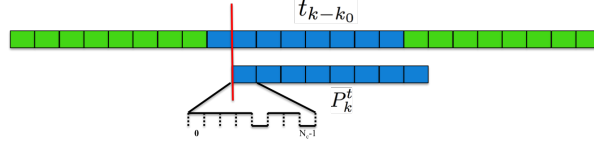


Figure 6: Chip-level Aligned

At this time

$$\begin{cases} \alpha = z & z \in \mathbb{Z} \\ \beta = 0 \end{cases} \Rightarrow k_0 = z \cdot N_c \quad (55)$$

For  $g_{k_0}^t$ :

$$g_{k_0}^t = \sum_{k'=0}^{N_f-1} t_{k'-k_0} \cdot h_{k'} \quad (56)$$

$$= \sum_{k'=0}^{N_f-1} D_{\lfloor (k'-k_0)/N_c \rfloor \% N_s}^t P_{k' \% N_c}^t \cdot h_{k'} \quad (57)$$

$$= \sum_{k'=0}^{N_f-1} D_{\lfloor (k'-z \cdot N_c)/N_c \rfloor \% N_s}^t P_{k' \% N_c}^t \cdot D_{\lfloor k'/N_c \rfloor}^t P_{k' \% N_c}^t \quad (58)$$

$$= \sum_{k'=0}^{N_f-1} D_{(\lfloor k'/N_c \rfloor - z) \% N_s}^t D_{\lfloor k'/N_c \rfloor}^t \underbrace{P_{k' \% N_c}^t P_{k' \% N_c}^t}_{\equiv 1} \quad (59)$$

$$= \sum_{k'=0}^{N_f-1} D_{(\lfloor k'/N_c \rfloor - z) \% N_s}^t D_{\lfloor k'/N_c \rfloor}^t \quad (60)$$

$$= C_z^{N_s-1}(D_k^t, D_k^t, z) + C_{N_s-z}^{N_s-1}(D_k^t, D_k^t, N_s - z) \quad (61)$$

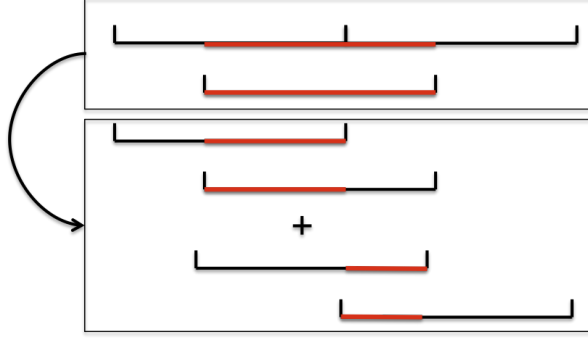


Figure 7: Diagram for Misaligned Convolution

For  $g_{k_0}^d$ :

$$\mathbb{E}\{g_{k_0}^d\} = \mathbb{E}\left\{\sum_{k'=0}^{N_f-1} D_{\lfloor k'/N_c \rfloor - z}^d P_{k' \% N_c}^d \cdot D_{\lfloor k'/N_c \rfloor \% N_s}^t P_{k' \% N_c}^t\right\} \quad (62)$$

$$= \sum_{k'=0}^{N_f-1} \mathbb{E}\{D_{\lfloor k'/N_c \rfloor - z}^d P_{k' \% N_c}^d \cdot D_{\lfloor k'/N_c \rfloor \% N_s}^t P_{k' \% N_c}^t\} \quad (63)$$

$$= \sum_{m=0}^{N_c} (P_m^d P_m^t) \sum_{m=\lfloor k'/N_c \rfloor}^{\lfloor k'/N_c \rfloor + N_s - 1} D_m^t \mathbb{E}\{D_{m-z}^d\} \quad (64)$$

$$= C_0^{N_c}(P_k^d, P_k^t, 0) \cdot \sum_{m=\lfloor k'/N_c \rfloor}^{\lfloor k'/N_c \rfloor + N_s - 1} D_m^t \cdot 0 \quad (65)$$

$$= 0 \quad (66)$$

$$\mathbb{E}\{(g_{k_0}^d)^2\} = \mathbb{E}\left\{\sum_{k'=0}^{N_f-1} D_{\lfloor k'/N_c \rfloor - z}^d P_{k' \% N_c}^d \cdot D_{\lfloor k'/N_c \rfloor \% N_s}^t P_{k' \% N_c}^t\right\}^2 \quad (67)$$

$$= (C_0^{N_c}(P_k^d, P_k^t, 0))^2 \mathbb{E}\left\{\sum_{m=\lfloor k'/N_c \rfloor}^{\lfloor k'/N_c \rfloor + N_s - 1} D_{m-z}^t D_m^d\right\}^2 \quad (68)$$

$$= (C_0^{N_c}(P_k^d, P_k^t, 0))^2 \mathbb{E}\left\{\sum_{m=\lfloor k'/N_c \rfloor}^{\lfloor k'/N_c \rfloor + N_s - 1} D_m^t D_m^d\right\}^2 \quad (69)$$

$$= (C_0^{N_c-1}(P_k^d, P_k^t, 0))^2 \cdot N_s \quad (70)$$

The mean and variance of  $g_{k_0}^d$  is the same as the situation of perfectly aligned.

### 2.2.3 Totally Misaligned

Totally Misaligned means the first chip of received data is not correspond to the first chip of patten. Like the Fig. 8



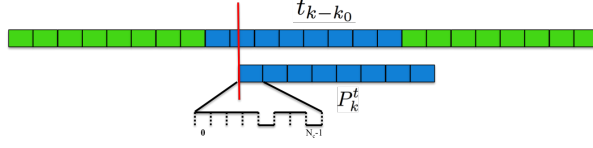


Figure 8: Totally Misaligned

$$k_0 = z, \quad z \in \mathbb{Z} \quad (71)$$

For  $g_{k_0}^t$ :

$$g_{k_0}^t = \sum_{k'=0}^{N_f-1} t_{k'-k_0} \cdot h_{k'} \quad (72)$$

$$= \sum_{k'=0}^{N_f-1} D_{[(k'-z)/N_c] \% N_s}^t P_{(k'-z) \% N_c}^t \cdot D_{[k'/N_c]}^t P_{k' \% N_c}^t \quad (73)$$

We will first deal with a smaller problem. If we only focus on patten of length  $N_c$  Define the result of the above situation to be  $f^t(s_1, s_2, t_1, z)$

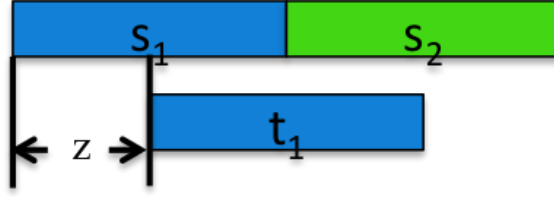


Figure 9: Chip-level Misaligned

$$f^t(s_1, s_2, t_1, z) = (s_1 \cdot t_1) C_z^{N_c-1}(P_k^t, P_k^t, z) + (s_2 \cdot t_1) C_{N_c-z}^{N_c-1}(P_k^t, P_k^t, N_c - z) \quad (74)$$

Now, back to  $g_{k_0}^t$

$$g_{k_0}^t = \sum_{m=\lfloor (-k_0)/N_c \rfloor, n=0}^{\lfloor m=(-k_0)/N_c \rfloor + N_s, n=N_s} f_{m \% N_s, m+1 \% N_s, n, z \% N_c}^t \quad (75)$$

For  $g_{k_0}^d$

$$\mathbb{E}\{g_{k_0}^d\} = \sum_{k'=0}^{N_f-1} D_{[(k'-z)/N_c] \% N_s}^d P_{(k'-z) \% N_c}^d \cdot D_{[k'/N_c]}^d P_{k' \% N_c}^d \quad (76)$$

We can also define

$$f_1^d(s_1, s_2, t_1, z) = (s_1 \cdot t_1) C_z^{N_c-1}(P_k^d, P_k^d, z) + (s_2 \cdot t_1) C_{N_c-z}^{N_c-1}(P_k^d, P_k^d, N_c - z) \quad (77)$$

Then  $g_{k_0}^d$  would be

$$g_{k_0}^d = \sum_{m=\lfloor (-k_0)/N_c \rfloor, n=0}^{\lfloor m=(-k_0)/N_c \rfloor + N_s, n=N_s} f^d(m, m+1, n, z \% N_c) \quad (78)$$

But for the expectation, we may need to change a little bit. Because we want to split the patten symbol rather than the received symbol.

$$g_{k_0}^d = \sum_{m=\lfloor (-k_0)/N_c \rfloor, n=0}^{\lfloor m=(-k_0)/N_c \rfloor + N_s, n=N_s} f^d(n, n+1, m, z \% N_c) \quad (79)$$

Then

$$\mathbb{E}\{g_{k_0}^d\} = \mathbb{E}\left\{ \sum_{m=\lfloor (-k_0)/N_c \rfloor, n=0}^{\lfloor m=(-k_0)/N_c \rfloor + N_s, n=N_s} f^d(n, n+1, m, z \% N_c) \right\} \quad (80)$$

$$= \sum_{m=\lfloor (-k_0)/N_c \rfloor, n=0}^{\lfloor m=(-k_0)/N_c \rfloor + N_s, n=N_s} \mathbb{E}\{f^d(n, n+1, m, z \% N_c)\} \quad (81)$$

$$= 0 \quad (82)$$

$$\mathbb{E}\{(g_{k_0}^d)^2\} = \left( C_{z \% N_c}^{N_c-1}(P_k^d, P_k^t, z \% N_c) + C_0^{z-1}(P_k^d, P_k^t, -z \% N_c) \right)^2 \cdot N_s \quad (83)$$

Because we can view it as a shifted training patten.