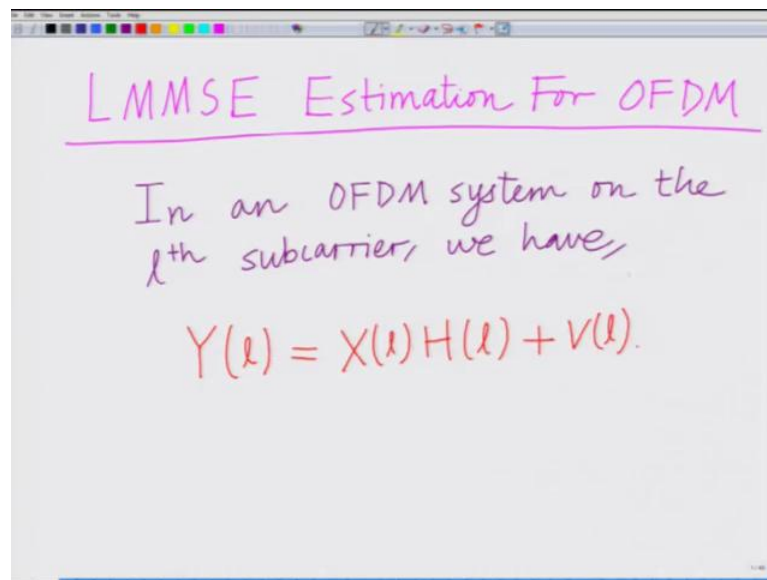


Bayesian/MMSE Estimation for MIMO/OFDM Wireless Communications
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Lecture – 32
LMMSE Estimation of OFDM Channel Coefficient Across
Each Subcarrier – Part I

Hello, welcome to another module. So, in this module we are going to look at LMMSE estimation for an OFDM Wireless Communication System, alright.

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So, we would like to look at the linear minimum means squared error estimation for OFDM. Which we already know is orthogonal frequency division multiplex you know, in OFDM system on the l^{th} subcarrier on the l^{th} subcarrier, we have well what we have? We have y_l equals x_l into H_l plus V_l well, what is l l denotes your index of the subcarrier l is basically the l^{th} subcarrier that we have talking about y_l is the symbol that is received of l^{th} subcarrier H_l is the channel coefficient corresponding to the l^{th} subcarrier x_l is the symbol transmitted or loaded on the l^{th} subcarrier and V_l is the noise of the l^{th} subcarrier.

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l^{th} subcarrier, we have,

$$Y(l) = X(l)H(l) + V(l)$$

l^{th} subcarrier

Estimate Channel Coefficient $H(l)$ for the l^{th} subcarrier.

Properties of $V(l)$.

And we have to estimate the channel coefficient on the estimate the channel coefficient H_l for the for the l th subcarrier. So, that is we have to do and towards doing that let us first start by talking about the statistics of the noise that is V_l . So, first let us start with the properties of the noise, let us start deriving the properties just start by deriving the properties of this noise component the noise sample capital V_l on the sub category lets.

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Properties of $V(l)$.

Let the time domain noise samples $V(0), V(1), \dots, V(N-1) \leftarrow$ IID Gaussian of mean = 0, variance = σ^2

$$E\{V(k)\} = 0$$
$$E\{|V(k)|^2\} = \sigma^2$$
$$E\{V(k)V^*(\tilde{k})\} = 0 \text{ if } k \neq \tilde{k}$$

Let assume the time domain noise samples let the time domain noise samples V_0, V_1 up to remember we have up to V_{n-1} , this are the n time domain noise sample let these be I i d Gaussian of mean equal to 0 and variance equal to σ^2 what; that means, at these noise samples a small V_k that is we have expected value of V_k equal to 0 expected value of magnitude V_k^2 that is the small V_k magnitude V_k^2 equals σ^2 and since they are independent expected value of V_k into v conjugate k tilde equals to 0. If k is not equal to k tilde, So, these we know about time domain samples of small V_k .

Now, what can say about the capital V_l right, which is the noise output on the l th subcarrier remember the capital V_l which are given by the FFT of the noise samples correct.

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The image shows a handwritten derivation on a whiteboard. At the top, it states $E\{V(k)V(k)\} = 0$. Below that, the equation $V(l) = \sum_{k=0}^{N-1} V(k) e^{-j2\pi k l / N}$ is written. A purple arrow points from the $V(l)$ term to the text " l th FFT pt of time Domain noise samples". Another purple arrow points from the N in the denominator to the text " $N = \#$ of subcarriers". At the bottom, it says " $V(l)$ is a Linear Combination of $V(k)$ ".

So, each capital V_l you can recall is the l th FFT point of the noise sample is the summation k equal to 0 to $n-1$ $V_k e^{-j2\pi k l / n}$. Where n equals your number of, So where n equals the number of subcarriers. Now, let us find. So, this V_l is the l th FFT point of the noise samples of your time domain the l th FFT point of the time domain noise samples. Now first observe that V_l is a linear combination that is capital V_l is a linear combination of the small. So, V_l is a the capital V_l is a linear

combination of V_k which have the time domain noise sample and this is the small V_k s are Gaussian right linear combination of Gaussian noise sample, Gaussian sample, Gaussian random variable is the Gaussian random variable. Therefore, since the capital V_l is the linear combination of the time domain noise sample of small V_k capital V_l is intern Gaussian noise sample alright this therefore, this implies linear combination of V_k this implies V_l is also V_l is a also a Gaussian random variant alright that is the first 1.

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The image shows a whiteboard with handwritten mathematical derivations. At the top, a green note reads: "in FFT pt Subcarrier of time Domain noise samples." A purple arrow points from this note to the main derivation. The main text in purple ink states: " $V(l)$ is a Linear Combination of $V(k) \Rightarrow V(l)$ is also Gaussian". Below this, the expectation of $V(l)$ is calculated as follows:

$$E\{V(l)\} = E\left\{\sum_{k=0}^{N-1} V(k) e^{-j2\pi kl/N}\right\}$$

$$= \sum_{k=0}^{N-1} \underbrace{E\{V(k)\}}_0 e^{-j2\pi kl/N}$$

$$E\{V(l)\} = 0$$

Further if you look at the expected value of V_l that is the nothing, but the expected value of summation k equals to 0 to n minus 1 $V_k e$ to the power of minus $j 2 \pi k$ lower n taking the expectation operator inside this is summation k equal to 0 to n minus 1 expected value of $V_k e$ to the power of minus $j 2 \pi k$ 1 divided by n each V_k is 0 mean expected value of V_k is 0 which means expected value of V_l is also 0.

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$$= \sum_{k=0}^{N-1} \underbrace{E\{V(k)\}}_0 e^{j2\pi kN}$$
$$E\{V(l)\} = 0$$

zero-mean

variance?

$$E\{|V(l)|^2\} = ?$$
$$= E\{V(l)V^*(l)\}$$

Therefore we can now say that V_l is Gaussian. So, we have deduce 2 proprieties 1, V_l is Gaussian V_l is also a 0 mean random variable, there is a noise output V_l on the l subcarrier is both Gaussian and it is 0 mean now I remains to deduce the variance of each that is, what is expected value of now, we want to ask the question what is the variance of each V_l that is expected value of magnitude of V_l square what is this remember this is also equals to expected value of magnitude of V_l v conjugate of l and I can simplify this as follows expected value of V_l into v conjugate of l .

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The image shows a whiteboard with handwritten mathematical equations. At the top, there is a red equation: $\langle \rangle = E \{ V(l) V^*(l) \}$. Below it, the derivation is written in purple and blue ink:

$$E \{ V(l) V^*(l) \}$$

$$= E \left\{ \left(\sum_{k=0}^{N-1} V(k) e^{-j2\pi k l / N} \right) \left(\sum_{\tilde{k}=0}^{N-1} V(\tilde{k}) e^{-j2\pi \tilde{k} l / N} \right)^* \right\}$$

$$= E \left\{ \sum_{k=0}^{N-1} \sum_{\tilde{k}=0}^{N-1} V(k) V^*(\tilde{k}) e^{-j2\pi (k - \tilde{k}) l / N} \right\}$$

This is equal to well expected value of we know the expression for $V(l)$ summation k equal to 0 to n minus one $V_k e$ to the power of minus $j 2 \pi k l$ divided by n into its own conjugate. Now I am going to write the conjugate with the different index k is a only a index. So, I going to use here an index k tilde k tilde equal to 0 to n minus 1 V_k tilde e to the power of minus $j 2 \pi k$ tilde l divided by n of course, the conjugate.

Now, I am going to simplify this together by multiplying out these 2 the term in these 2 brackets term by term. So, I have k equal to 0 to n minus 1 summation k tilde equal to 0 to n minus one $V_k v k$ tilde conjugate e to the power of minus $j 2 \pi k$ minus k tilde l by n .

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$$\begin{aligned}
 &= E \left\{ \sum_{k=0}^{N-1} \sum_{\tilde{k}=0}^{N-1} v(k) v^*(\tilde{k}) e^{-j2\pi(k-\tilde{k})\frac{l}{N}} \right\} \\
 &= \sum_{k=0}^{N-1} \sum_{\tilde{k}=0}^{N-1} E \{ v(k) v^*(\tilde{k}) \} e^{-j2\pi(k-\tilde{k})\frac{l}{N}} \\
 &\quad \begin{aligned}
 &\quad \downarrow = 0 \text{ if } k \neq \tilde{k} \\
 &\quad = \sigma^2 \text{ if } k = \tilde{k}
 \end{aligned} \\
 &= \sum_{k=0}^{N-1} \sigma^2 e^{-j2\pi \cdot 0 \cdot \frac{l}{N}} \\
 &= \sum_{k=0}^{N-1} \sigma^2 = N\sigma^2
 \end{aligned}$$

Now, once we take the expectation operator inside I have something interesting I have summation k equal to 0 to n minus 1 k tilde equal to 0 equal to n minus 1 expected value of $V_k v$ conjugate k tilde e to the power of minus j 2 pi k minus k tilde l divided by n and now, we that these 2 noise samples that the time domain noise sample the small v ks are independent which means expected value of that is what we have already seen expected value of V_k times, V_k tilde conjugate equal 0. If k is not equal to k tilde and sigma square if k is equal to k tilde alright.

So, this is equal to equal to 0, if k is not equal to k tilde equal to sigma square if only if k is equal to k tilde which means only terms which survive in the summation are when k is equal to k tilde and therefore, this is for each k only one term corresponding to when k tilde equal to k will survive. So, this will be summation k and when k equal to k tilde this sigma square. So, this is summation k equal to 0 to n minus one sigma square e to the power of minus j 2 pi k minus k tilde is 0 divided by n which is basically 1 e to the power of 0 is 1. So, this is summation k equal to 0 to n minus 1 sigma square which is equal to sigma square.

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The image shows a whiteboard with handwritten mathematical derivations. The first line is $= \sum_{k=0}^{N-1} \sigma^2 e^{j2\pi k/N}$. The second line is $= \sum_{k=0}^{N-1} \sigma^2 = N\sigma^2$. The third line is $E\{|V(l)|^2\} = N\sigma^2$. Below this, there is a note: $V(l)$ is Gaussian, with mean = 0 and variance = σ^2 .

Therefore what we have is if you look at this result we have expected value of magnitude V_l square equals n sigma square. So, V_l is Gaussian that is written by the symbol n its normal Gaussian is; in fact, complex Gaussian. So, let simply write V_l is Gaussian mean equals 0 variance is equal to sigma square its mean equal to 0 and variance is equal to sigma square correct right, v_l . So, we have characterized the noise the properties of this noise V_l then V_l is remember this is the noise coefficient across the remember, we need this properties to in order to find the IMMSE estimate because IMMSE estimate depends on the depends on knowing remember we need to know the variance alright the mean and the variance of the noise.

Now, let us go back and let us look characterize the prior variance let us characterize the properties of the channel coefficient H_l corresponding to subcarrier l . So, we would like to characterize the properties of the channel coefficient H_l .

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LMMSE Estimation For OFDM

In an OFDM system on the l^{th} subcarrier, we have,

$$Y(l) = X(l)H(l) + V(l)$$

$Y(l)$ is labeled as l^{th} subcarrier. $V(l)$ is circled in red and labeled "Properties:". $H(l)$ is underlined and labeled "Estimate Channel Coefficient $H(l)$ for the l^{th} subcarrier." A red arrow points from the equation to the text "D. ... of $V(l)$ ".

So, we would like to characterize the properties of the channel coefficient $H(l)$ now remember $H(l)$?

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variance = σ^2

$$H(l) = \sum_{k=0}^{L-1} h(k) e^{-j2\pi k l / N}$$

l^{th} FFT coefficient of channel taps $h(0), h(1), \dots, h(L-1)$

Let these channel taps be zero-mean IID, var = σ_h^2

Now, let now remember $H(l)$ again similar to the noise $H(l)$ is the l^{th} FFT coefficient of the channel taps $h(k)$ there is summation k equal to 0 to $L-1$ $h(k) e^{-j2\pi k l / N}$

this is the l th FFT coefficient of channels taps h_0, h_1, \dots, h_{L-1} now what we are going to assume is.

We are going to assume let these channel taps let these channel taps h_k , let these channel taps be 0 mean I i d variance is equal to σ_h^2 that is we are assuming the channel taps where $0 \leq k \leq L-1$ to be independent identically distributed with mean 0 and variance σ_h^2 as we know because, we considering the IMMSE estimate these need not necessarily be Gaussian in nature right. If we are considering the IMM if they are additionally Gaussian then this becomes the MMSE estimate alright. So, for a general IMMSE estimation scenario these need not be Gaussian.

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Let these channel taps be zero-mean IID, var = σ_h^2

$$E\{h(k)\} = 0$$

$$E\{|h(k)|^2\} = \sigma_h^2$$

$$E\{h(k)h^*(\tilde{k})\} = 0 \text{ if } k \neq \tilde{k}$$

$$E\{H(l)\} = E\left\{\sum_{k=0}^{N-1} h(k) e^{-j2\pi k l / N}\right\}$$

$$= \sum_{k=0}^{N-1} \underbrace{E\{h(k)\}}_0 \cdot e^{-j2\pi k l / N}$$

So, we are assuming expected that is the channel taps the small h s remember these are the channel taps expected h_k equal to 0 expected magnitude h_k square equals σ_h^2 expected magnitude h_k into $h_{\tilde{k}}$ conjugate equals to 0 because they are independent if $k \neq \tilde{k}$; obviously, if $k = \tilde{k}$ then, this becomes σ_h^2 alright.

Now, again we have $H(l) = \sum_{k=0}^{N-1} h_k e^{-j2\pi k l / N}$. If I take the expected value on the left I also get the expected value on the

right which is equal to, now taking the expected value inside expectation operator inside k is equal to 0 to n minus 1 expected value of h k e raise to minus j 2 pi k l by n expected value of each h k equals 0 because we assuming the these 2 0 mean random variables.

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The image shows a whiteboard with handwritten mathematical derivations. The first line states $E\{H(l)\} = 0$ and notes that $H(l)$ is zero-mean. The second line shows $E\{H(l) \cdot H^*(l)\} = E\{|H(l)|^2\}$. The third line expands this as $E\left\{\left(\sum_{k=0}^{N-1} h(k) e^{-j2\pi k l / N}\right) \left(\sum_{\tilde{k}=0}^{N-1} h(\tilde{k}) e^{-j2\pi \tilde{k} l / N}\right)^*\right\}$. The final line shows the expanded form: $E\left\{\sum_{k=0}^{N-1} \sum_{\tilde{k}=0}^{N-1} h(k) h(\tilde{k}) e^{j2\pi(k-\tilde{k})l / N}\right\}$.

Therefore expected value of H_l where H_l is the l th channel coefficient on the l th subcarrier expected value of each H_l is also 0. So, which means this each H_l is also implies H_l that coefficient on the l th subcarrier channel coefficient on the l th subcarrier is also 0 mean.

Now, we have to the variance that is what is the expected value of $H_l h$ conjugate l which is the expected value of magnitude H_l square expected value of H_l into h conjugate l which is expected value of magnitude H_l square what is this? This is equals to the expected value of well let us again write at use the same trick or technique that we used earlier we can write this as expected value of summation k equals to 0 to n minus 1 $h k$ e raise to minus $j 2 \pi k l$ divided by n into same thing, but changing the index k tilde equals to 0 to n minus one $h k$ tilde e raise to minus $j 2 \pi k$ tilde l divided by n conjugate which is equal to well.

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The image shows a whiteboard with handwritten mathematical equations. At the top, there are two summation indices, $k=0$ and $\tilde{k}=0$, with arrows pointing to them. The main equation is:

$$= \sum_{k=0}^{L-1} \sum_{\tilde{k}=0}^{L-1} E\{h(k)h^*(\tilde{k})\} e^{-j2\pi(k-\tilde{k})/N}$$

A note above the expectation operator says "Taking Expectation operator inside". Below the expectation operator, there are two cases:

$$= 0 \text{ if } k \neq \tilde{k}$$

$$= \sigma_h^2 \text{ if } k = \tilde{k}$$

The equation then simplifies to:

$$= \sum_{k=0}^{L-1} \sigma_h^2 \cdot e^{-j0}$$

Finally, it simplifies to:

$$= \sum_{k=0}^{L-1} \sigma_h^2 = L\sigma_h^2$$

Now, multiplying term by term summation k equal to 0 to n minus 1 k tilde equals to 0 to n minus 1 $h(k)h^*(\tilde{k})$ $e^{-j2\pi(k-\tilde{k})/N}$ taking the expectation operator inside alright taking the expectation operator this gives summation k equal to 0 summation k tilde equals to 0 expected value of. Of course, there has to be conjugated expected value of $h(k)h^*(\tilde{k})$ $e^{-j2\pi(k-\tilde{k})/N}$ and now, you can see this sorry this can only be an one point FFT sorry this has to be because, there are only 1 channel taps this can only be till $L-1$ this can only be till $L-1$ or the summations are only till $L-1$ because we have only 1 channel taps.

So, this is still $L-1$ $L-1$ $L-1$ and again this is also till $L-1$ this also till $L-1$ and you realize that this is equal to 0. If k is not equal to k tilde equal to σ_h^2 if k is equal to k tilde hence the only term, which survive are the once is k is equal to k tilde again similar to the previous derivation. Therefore, this will again be summation k equal to 0 to $L-1$ σ_h^2 again e^{-j0} equals summation k equal 0 to $L-1$ σ_h^2 which is L times σ_h^2 .

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$$\begin{aligned} &= \sum_{k=0}^{L-1} \sigma_h^2 \cdot e^{j\theta} \\ &= \sum_{k=0}^{L-1} \sigma_h^2 = L\sigma_h^2 \end{aligned}$$
$$\boxed{E\{|H(l)|^2\}} = L\sigma_h^2$$

variance of $H(l)$

Channel coefficient of l^{th} subcarrier.

Therefore, what we have now is basically we have expected value of magnitude $|H(l)|^2$ square equals $L\sigma_h^2$. So, we have the variance of the channel coefficient on the l^{th} subcarrier assuming IID channel taps h_0, h_1, \dots, h_{L-1} that is assuming one IID channel taps h_0, h_1, \dots, h_{L-1} . So, this is the variance, variance of the channel coefficient h_l is the channel coefficient of the l^{th} channel coefficient of the l^{th} subcarrier, alright.

So, what we have done today is we have consider the OFDM system model accuracy is subcarriers assumed IID time domain noise sample 0 mean variance σ^2 , derive the properties of the noise V_l at the output of the FFT and we have shown that the noise V_l on the each subcarrier is Gaussian 0 mean, variance n times σ^2 and we also assumed IID, one IID channel taps and demonstrated channel that the channel coefficient H_l is also 0 mean and has a variance $L\sigma_h^2$ alright we are going to use these properties in the subsequent module to compute the MMSE estimate of the channel coefficient H_l on subcarrier l . So, we will stop here.

Thank you.