

Bayesian/MMSE Estimation for MIMO/OFDM Wireless Communications
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Lecture – 33

IMMSE Estimation of OFDM Channel Coefficient Across Each Subcarrier-Part II

Hello, welcome to another module. We are deriving the IMMSE estimate of the channel coefficient in of dm system that is considering each sub carrier we are deriving the IMMSE estimate of the channel coefficient corresponding to that particular sub carrier.

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The image shows a whiteboard with the following handwritten content:

$$Y(l) = \overline{H(l)}X(l) + \overline{V(l)}$$

Below the equation, the following statistical properties are listed:

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

$$E\{|H(l)|^2\} = L\sigma_h^2$$

where $L = \text{Number of channel taps}$.

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

$$E\{|V(l)|^2\} = N\sigma_v^2$$

where $N = \text{number of subcarriers}$.

So, across sub carrier l right, we have Y_l equals H_l where H_l is the channel coefficient times x_l plus V_l right V_l is the noise corresponding to sub carrier l . We have seen that H_l is basically such that expected assuming 0 mean IID taps of variance σ_h^2 each we have seen expected value of H_l is 0. The variance expected value of magnitude H_l square equals $L\sigma_h^2$. We have also seen assuming IID Gaussian noise samples 0 mean of variance σ_v^2 each expected capital V_l the noise sample on each sub carrier this is equal to 0 expected value of magnitude V_l square, this is equal to what is this equal to this is equal to well N times

sigma square, what is l? l equals to number of channel taps and n is equal to number of sub carrier this we have seen. So, far we have seen, alright.

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Channel Coefficient $L = \text{Number of channel taps}$
 $H(l)$, Noise $V(l)$ are independent

$$E\{H(l)V^*(l)\} = 0$$

$$E\{V(l)H^*(l)\} = 0$$

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

$$\hat{H}(l) = \Gamma_{H(l)Y(l)} \Gamma_{Y(l)Y(l)}^{-1} Y(l)$$

LMMSE Estimate of $H(l)$.

Let us now assume that this channel coefficient $H(l)$ and the noise $V(l)$ are independent. So, we are assuming going to assume, that similar to what we have assumed before that is correct the channel coefficient h , that these channel coefficient and noise $V(l)$ are independent. And we have already justified this several times before we said the channel coefficient arises because of the properties of the ambient scattering environment. the noise arises because of the thermal noise process and the receiver and these 2 phenomena are independent all right. Therefore, the channel coefficient and the noise are can be assume to be independent all right that is a realistic or a realistic and in fact, a very practical assumption. So, we can say that expected value of $H(l)$ terms v conjugate l equals zero. In fact, expected value of $V(l)$ times h conjugate l is also 0.

Now, coming back to our modal that is $Y(l)$ equals $H(l) \times l$ plus $V(l)$, we indeed we can compute the MMSE estimate \hat{h} of l as $\Gamma_{H(l)Y(l)}$, remember this is the standard expression that is the cross covariance.

Where H_l Y_l into r the covariance of Y_l inverse times Y_l this is the standard expression remember, this is the IMMSE estimate of the channel coefficient H_l all right this the r H_l Y_l r H_l Y_l which is the correlation between H_l and Y_l times r Y_l Y_l inverse, where r Y_l y l is basically the covariance of the output Y_l of the l sub carrier times Y_l where Y_l is the output of the l th sub carrier all right this is basically follows from the expression for the standard IMMSE estimate all right the principle of standard IMMSE estimation all right.

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$$\begin{aligned}
 \Gamma_{Y_l Y_l} &= E \{ Y_l Y_l^* \} \\
 &= E \{ (H_l X_l + V_l) \times (H_l X_l + V_l)^* \} \\
 &= E \{ (H_l X_l + V_l) \times (H_l^* X_l^* + V_l^*) \}
 \end{aligned}$$

Now, what remains is basically to compute each of these quantities is Y_l y l equals expected value of Y_l times y conjugate l . This is equal to well substitute Y_l expected Y_l is basically your H_l x l plus V_l times H_l x l plus V_l conjugate this is equal to the expected value of well H_l . Let us just write a couple more steps in between to be very clear H_l x l plus V_l into h conjugate l x conjugate l plus v conjugate l .

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$$\begin{aligned}
 & \left(H(l)X^*(l) + V(l) \right) \\
 = & E \left\{ |H(l)|^2 |X(l)|^2 + V(l)H^*(l)X^*(l) \right. \\
 & \left. + H(l)X(l)V^*(l) + |V(l)|^2 \right\} \\
 = & E \left\{ |H(l)|^2 \right\} |X(l)|^2 + E \left\{ V(l)H^*(l) \right\} X^*(l) \\
 & + E \left\{ H(l)V^*(l) \right\} X(l) + E \left\{ |V(l)|^2 \right\}
 \end{aligned}$$

And now I can expand this as expected value of well Hl, we have the first term Hl x l h conjugate l x conjugate l that is magnitude Hl square magnitude xl square plus Vl into h conjugate l h conjugate l into x conjugate l plus well plus Hl x l into v conjugate l plus Vl into v conjugate l that is magnitude v conjugate a magnitude Vl whole square.

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$$\begin{aligned}
 & + H(l)X(l)V^*(l) + |V(l)|^2 \\
 = & \underbrace{E \left\{ |H(l)|^2 \right\}}_{L\sigma_h^2} |X(l)|^2 + \underbrace{E \left\{ V(l)H^*(l) \right\}}_0 X^*(l) \\
 & + \underbrace{E \left\{ H(l)V^*(l) \right\}}_0 X(l) + \underbrace{E \left\{ |V(l)|^2 \right\}}_{N\sigma_v^2} \\
 = & L\sigma_h^2 |X(l)|^2 + N\sigma_v^2 = r_Y(l)Y(l).
 \end{aligned}$$

And now I can simplify this as well term by term taking expected value of magnitude H_l square into magnitude x_l square plus expected value of V_l conjugate l times conjugate l plus expected value of H_l into v conjugate l into x_l plus expected value of magnitude V_l square.

Now, we know that expected value of $V_l H_l$ conjugate is 0 expected value of $H_l V_l$ conjugate this is 0 because the noise and the channel coefficient are uncorrelated expected value of magnitude H_l square this is 1 times σ_h square this, we already known already known expected value of V_l square is n times σ_x square therefore, what we have is 1 times σ_h square times magnitude x_l square plus n times σ_x square that is your $r_{Y_l Y_l}$ which is the covariance of which is the covariance right which is the covariance of the channel coefficient, which the is covariance of the channel coefficient y are the observation Y_l across the on the l th sub care all right and now we need to.

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The image shows a handwritten derivation of the covariance $r_{H(l)Y(l)}$. The steps are as follows:

$$\begin{aligned}
 r_{H(l)Y(l)} &= E\{H(l)Y^*(l)\} \\
 &= E\{H(l)(H(l)X(l) + V(l))^*\} \\
 &= E\{H(l)(H^*(l)X^*(l) + V^*(l))\} \\
 &= \underbrace{E\{|H(l)|^2\}}_{L\sigma_h^2} X^*(l) + \underbrace{E\{H(l)V^*(l)\}}_0 \\
 &= L\sigma_h^2 X^*(l)
 \end{aligned}$$

Compute $r_{H_l Y_l}$ which is the cross correlation between the channel coefficient H_l and observation Y_l and that can be also be computed in a straight forward passion as follows $r_{H_l Y_l}$ equals expected value of H_l into Y_l conjugate equals expected value of H_l times $H_l x_l$ plus V_l , conjugate equals expected value of well H_l into h conjugate l x , conjugate

$1 + v \text{ conjugate } 1$ which is equal to which is equal to expected value of well magnitude H_l square $x \text{ conjugate } 1$ plus expected value of $H_l v \text{ conjugate } 1$ which is 0 expected value of magnitude $1 \text{ conjugate } H_l$ h magnitude H_l square is $1 \text{ sigma } h$ square. So, this is simply $1 \text{ sigma } h$ square $x \text{ conjugate } 1$ where remember x is the pilot.

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$$= L \sigma_h^2 X^*(l)$$

$$X(l) = \text{Pilot Symbol loaded on the } l^{\text{th}} \text{ subcarrier}$$

$$\hat{H}(l) = \Gamma_{H(l)Y(l)} \Gamma_{Y(l)Y(l)}^{-1} Y(l)$$

$$= L \sigma_h^2 X^*(l) \cdot \frac{1}{L \sigma_h^2 |X(l)|^2 + N \sigma^2} Y(l)$$

Symbol transmitted or loaded on the l th sub carrier x l equals pilot symbol loaded on the l th sub carrier. This is the pilot symbol remember we transmit pilot symbols specifically for the purpose of channel estimation and this is pilot symbol that is loaded.

On the l th sub carrier therefore, now substituting therefore, we have computed both the quantities r h y and r y y .

Now, substituting an expression for the IMMSE estimate we have the IMMSE estimate that is given as \hat{h}_l equals r H_l Y_l r Y_l Y_l inverse into Y_l now r H_l Y_l is $1 \text{ sigma } h$ square x 1 conjugate into r Y_l Y_l inverse is basically into 1 , over where r Y_l y l is basically your that is that is basically your $1 \text{ sigma } h$ square magnitude x 1 square plus $n \text{ sigma}$ square times Y_l .

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$X(l) =$ Pilot Symbol loaded on the l^{th} subcarrier

$$\hat{H}(l) = \Gamma_{H(l)Y(l)} \Gamma_{Y(l)Y(l)}^{-1} Y(l)$$

$$= L \sigma_h^2 X^*(l) \cdot \frac{1}{L \sigma_h^2 |X(l)|^2 + N \sigma_n^2} Y(l)$$

$$\hat{H}(l) = \frac{L \sigma_h^2 X^*(l)}{L \sigma_h^2 |X(l)|^2 + N \sigma_n^2} Y(l)$$

MMSE Estimate of $H(l)$

Now, I can write this estimate as your $\hat{H}(l)$ equals well $L \sigma_h^2$ divided by $L \sigma_h^2$ plus $N \sigma_n^2$ into $L \sigma_h^2$ x conjugate $X(l)$ divided by $L \sigma_h^2$ plus $N \sigma_n^2$ into $Y(l)$ that is the output on the l^{th} sub carrier and if you look at this, this is the expression for the once again MMSE estimate of $H(l)$ this is the MMSE estimate of $H(l)$ and once again you can see in this expression for the MMSE estimate. So, we have derived the expression for the MMSE estimate you can see once again for the expression for the MMSE estimate that if at high SNR again similar to at high SNR.

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LMMSE Estimate of $H(l)$.

At High SNR
 $\Rightarrow L\sigma_h^2 |X(l)|^2 \gg N\sigma^2$

$$\hat{H}(l) \approx \frac{L\sigma_h^2 X^*(l) \cdot Y(l)}{L\sigma_h^2 |X(l)|^2}$$
$$\hat{H}(l) = \frac{1}{X(l)} \cdot Y(l)$$

\uparrow (ML estimate of $\hat{H}(l)$).

What do you mean by S SNR implies if $L\sigma_h^2$ magnitude $|X(l)|^2$ is much greater than $N\sigma^2$ then $\hat{H}(l)$ becomes approximately your, I can ignore $N\sigma^2$ in comparison to $L\sigma_h^2$ magnitude $|X(l)|^2$. So, this becomes $L\sigma_h^2$ well $X(l)$ conjugate l divided by $L\sigma_h^2$ magnitude $|X(l)|^2$.

Into $Y(l)$, but $X(l)$ magnitude $|X(l)|^2$ which is nothing, but $X(l)$ into $X(l)$ conjugate l therefore, this becomes well $1 \times \sigma_h^2$ σ_h^2 cancel. So, this becomes 1 over $X(l)$ into $Y(l)$ and this is simply the ml estimate that is this is simply the expression for the maximum like load ml estimate that is once again at high SNR that is when, your $L\sigma_h^2$ magnitude $|X(l)|^2$ is much, much greater than noise power $N\sigma^2$ on the sub carrier l . Then what happens it again reduces to the ml estimate the maximum likelihood estimate for the channel coefficient $H(l)$ which is simply $Y(l)$ that is the output of sub carrier l divided by $X(l)$ which is the capital $X(l)$ which is the symbol loaded on the sub carrier l .

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Error variance of LMMSE Estimate
 For OFDM system is,

$$E\{|\hat{H}(l) - H(l)|^2\}$$

$$= r_{H(l)H(l)} - r_{H(l)Y(l)} r_{Y(l)Y(l)}^{-1} Y(l)H(l)$$

Annotations:
 - "Already computed For LMMSE" points to $r_{Y(l)Y(l)}^{-1}$
 - $E\{|H(l)|^2\} = L\sigma_h^2$ points to $r_{H(l)H(l)}$
 - $E\{Y(l)H(l)^*\}$ points to $r_{H(l)Y(l)}$

Now we can again similarly find out what is the error what is the variance of the error corresponding to the estimate of channel coefficient l . So, let us now complete this problem find that finding the variance of that error the error variance the error variance of LMMSE estimate for the of dm system is well we have expected value of magnitude h hat l minus $H(l)$ whole square this is equal to $r_{H(l)H(l)} - r_{H(l)Y(l)} r_{Y(l)Y(l)}^{-1} r_{Y(l)H(l)}$ into $r_{Y(l)Y(l)}$ well $H(l)$.

Now if you can observe this this quantity is what we have exactly computed above that is $r_{H(l)Y(l)} r_{Y(l)Y(l)}^{-1}$ this is the quantity that, we computed for the already computed for LMMSE estimate this is the quantity that we have already computed. Now $r_{H(l)H(l)}$ this is nothing, but expected value of your magnitude $H(l)$ square and this is equal to $L\sigma_h^2$ and this quantity $r_{Y(l)Y(l)}$ expected value of $Y(l)$ into $H(l)$ conjugate this is nothing, but $r_{H(l)Y(l)}$ conjugate. We have already computed r and this is equal to basically $r_{Y(l)H(l)}$ that is basically your $r_{Y(l)H(l)}$ is basically r . if you look at this quantity $r_{Y(l)H(l)}$ this is expected value of $Y(l)$ into h conjugate l which is basically $r_{H(l)Y(l)}$ conjugate and we have computed all these quantities before that is $r_{H(l)Y(l)}$ and each of these quantities we have computed before.

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$$\begin{aligned}
 & \text{Re}\{H(\omega)Y(\omega)\} \\
 &= L\sigma_h^2 - \frac{L\sigma_h^2 X^*(\omega)}{L\sigma_h^2 |X(\omega)|^2 + N\sigma^2} \cdot (L\sigma_h^2 X(\omega))^* \\
 &= L\sigma_h^2 - \frac{(L\sigma_h^2)^2 |X(\omega)|^2}{L\sigma_h^2 |X(\omega)|^2 + N\sigma^2} \\
 &= L\sigma_h^2 \left\{ 1 - \frac{L\sigma_h^2 |X(\omega)|^2}{L\sigma_h^2 |X(\omega)|^2 + N\sigma^2} \right\}
 \end{aligned}$$

So, all it remains basically remains it remains to substitute these quantities which I am going to do now. So, $\text{Re}\{H(\omega)Y(\omega)\}$ that is basically your let me write this again $\text{Re}\{H(\omega)Y(\omega)\}$ that is equal to $L\sigma_h^2$ minus $L\sigma_h^2$ times $|X(\omega)|^2$ divided by $L\sigma_h^2 |X(\omega)|^2 + N\sigma^2$ times $|X(\omega)|^2$ which is $L\sigma_h^2$ times $|X(\omega)|^2$ divided by $L\sigma_h^2 |X(\omega)|^2 + N\sigma^2$.

And therefore, that gives us $L\sigma_h^2$ minus $L\sigma_h^2$ times $|X(\omega)|^2$ divided by $L\sigma_h^2 |X(\omega)|^2 + N\sigma^2$ times $|X(\omega)|^2$ which is equal to $L\sigma_h^2$ times $1 - \frac{|X(\omega)|^2}{|X(\omega)|^2 + \frac{N\sigma^2}{L\sigma_h^2}}$ and this is equal to well, if you look at this this is simply your $L\sigma_h^2$ times $\frac{|X(\omega)|^2 + \frac{N\sigma^2}{L\sigma_h^2} - \frac{N\sigma^2}{L\sigma_h^2}}{|X(\omega)|^2 + \frac{N\sigma^2}{L\sigma_h^2}}$ and this cancels.

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The image shows a whiteboard with handwritten mathematical expressions. At the top, there is a partial expression: $(L\sigma_h^2 |X(l)|^2 + N\sigma^2)$. Below it, the expression $= L\sigma_h^2 \cdot \frac{N\sigma^2}{L\sigma_h^2 |X(l)|^2 + N\sigma^2}$ is written. A red box encloses the following equation:
$$E\{\hat{H}(l) - H(l)\}^2 = \frac{1}{\frac{1}{N\sigma^2 |X(l)|^2} + \frac{1}{L\sigma_h^2}}$$
 An arrow points from the text "Expression For error variance of estimate" to the boxed equation.

So, what is left is $n \sigma^2$ divided by $l \sigma_h^2$ magnitude $|x_l|^2$ plus $n \sigma^2$. Now bringing $l \sigma_h^2$ and $n \sigma^2$ to the denominator what we have is this is equal to 1 over 1 divided by well $n \sigma^2$ divided by magnitude $|x_l|^2$ plus 1 over $l \sigma_h^2$ and this is basically your equals your expected value of magnitude h_k \hat{h}_k minus h_k whole square. So, what we get is this is equal to this quantity this is the expression for the error variance expression for error variance this is the expression, expression for error variance of estimates sorry this has to be \hat{h}_l that is the estimate of the l th sub carrier yeah magnitude \hat{h}_l minus H_l square still vary expression for the error variance of estimate \hat{h}_l corresponding to corresponding to sub carrier l .

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$$E\{|H(l) - \hat{H}(l)|^2\} = \frac{1}{\frac{1}{\frac{N\sigma^2}{|X(l)|^2}} + \frac{1}{L\sigma_h^2}}$$

Expression For error variance of estimate $H(l)$ corresponding to Subcarrier l .

$$\frac{1}{\text{ML MSE} + \text{Prior var}}$$

$$= \text{Harmonic Mean}(\text{ML MSE}, \text{Prior variance})$$

So, this is the expression for the error variance the variance of the error of estimate \hat{h} corresponding to the corresponding to sub carrier l and once again you can see, one over $l \sigma_l \sigma_h$ square is basically the prior variance that is $l \sigma_h$ square is basically the prior variance of H_l right. We have already seen that $n \sigma$ square is basically $n \sigma$ square divided by magnitude x_l square is the variance of what is the mean square error of the maximum likelihood estimate.

Therefore, again you can see it is the harmonic mean of the mean square error of the maximum likelihood estimate and the prior variance all right and this is something that we have seen several times before and once again well this is true of all IMMSE estimation in general. So, this is basically your again to reconfirm that one by ml MSE plus one by prior variance that is this is basically equal to your equal to the harmonic mean of MSE of m_l comma where m_l denotes the maximum likelihood estimate that is it is the harmonic mean of the mean square error of the maximum likelihood estimate and the prior variance of the channel coefficient.

So, basically this completes IMMSE estimate of IMMSE estimation of the channel coefficient H_l corresponding to sub carrier l and also the derivation of the variance or

derivation the mean squared error rather of the estimate of the IMMSE estimate all right we will continue in this subsequent module.

Thank you very much.