

Introduction To Adaptive Signal Processing

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Lecture No # 20

Application of Adaptive Filter (Contd.)

So, in the last class we are considering this problem, we were given a single suppose S_n which is the summation of p number of complex sinusoids, this one is S_{1n} and S_{pn} all right. We have seen in the previous class that $1 - e^{-j\omega c_1} z^{-1}$ this factor times S_{1z} equal to 0 dot dot dot dot in general $1 - e^{-j\omega c_1} z^{-1}$ may be $k z^{-1}$, S_{kz} equal to 0 that we have seen I am not re deriving. And therefore, if you take the product of this you call it Qz , you call it Qz , the product dot dot dot $1 - e^{-j\omega c_1} z^{-1}$ last one is. So, there are p such factors. So, if you take this Qz obviously Qz into Sz was 0, Qz into Sz was 0 because if you take this factor we have seen earlier or maybe just for real quick recalling you take this S_{1n} was a_1 say S_{kn} is $e^{-j\omega c_k n}$.

So, $S_{kn} - 1$ if you put $n - 1$ here it becomes $e^{-j\omega c_k (n - 1)}$ minus 1. So, one factor comes out rest is as it is. So S_{kn} which means, S_{kn} is $e^{-j\omega c_k n}$ $S_{kn} - 1$ if you take z transform on both sides here it is z^{-1} time S_{kz} it is S_{kz} and then take all the terms to one side, it will be into S_{kz} equal to 0. This for any S_{kz} and now I have taken the product of all of them and this overall polynomial into Sz is 0 because suppose I am considering this then this is a product of the factors. So, I can push take the this factor out and put it in the front.

Lecture-20: Application of Adaptive Filter (Contd.)

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Lecture 20

$$x_n(n) = A_1 e^{j\omega_{c1} n}$$

$$d_n(n) = e^{-j\omega_{c1} n} x_n(n)$$

$$\Rightarrow d_n(n) = e^{j\omega_{c1} n} x_n(n)$$

$$\Rightarrow (1 - e^{j\omega_{c1} n} z^{-1}) S_n(z) = 0$$

$$S(z) = \frac{A_1 e^{j\omega_{c1} n}}{A_1(n)} + \dots + \frac{A_p e^{j\omega_{cp} n}}{A_p(n)}$$

$$(1 - e^{j\omega_{c1} n} z^{-1}) S_1(z) = 0$$

$$(1 - e^{j\omega_{c2} n} z^{-1}) S_2(z) = 0$$

$$q(z) = (1 - e^{j\omega_{c1} n} z^{-1}) \dots (1 - e^{j\omega_{cp} n} z^{-1}) \dots (1 - e^{j\omega_{cp} n} z^{-1})$$

$$q(z) S(z) = 0$$

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So, then this times $S_1(z)$ I mean $S_1(z)$, so this first factor which is this into $S_1(z)$ that is 0 we have seen k equal to 1 so $1 - e^{j\omega_{c1} n} z^{-1}$ $S_1(z)$. So, that will be 0 if it is the k th sinusoid here then $Q(z)$ from $Q(z)$ I will take out the corresponding factor put it in the front. So, again $Q(z)$ times that $S_k(z)$ here will be 0 and so on and so forth and that is why $Q(z) S(z)$ is 0, but $Q(z)$ is a product of these factors. So, if you carry out the product it will be a p th order polynomial because p such first order factors multiplied and leading term is $1 \cdot 1 \cdot 1 \cdot 1$ so 1. So, it will be like $Q(z)$ will be like 1 then some coefficient maybe a_1 instead of plus a_1 I am just putting a minus a_1 .

If you carry out the product it will be some coefficient times z^{-1} minus dot dot dot minus $A_k z^{-k}$ minus dot dot dot minus $A_p z^{-p}$ because p th order polynomial so high I mean highest degree of z^{-1} is p z^{-1} into z^{-1} into z^{-1} p times minus I just deliberately put minus a_1 is the coefficient, minus A_k is the coefficient like this. So, this is my $Q(z) S(z) = 0$. So, $S(z)$ into 1 that you keep on one side and remaining terms you take to right hand side then if you take the inverse z transform $S(z)$ into 1 will give you S_n and then $a_1 z^{-1} S(z)$ which means in time domain $S_n - 1$, then

$a_2 z^{-2} S_z$ so $a_2 S_n$ minus 2 and dot dot dot lastly $A_p S_z A_p z^{-p} S_z z^{-p}$ means is in time domain S_n minus p so $A_p S_n$ minus p . It means if it is a summation of p sinusoids complex sinusoids these are called not cos and sin but complex sinusoids if it is a sum if the single is a sum of p sinusoids. Then any current sample will be exactly expressible you can write it exactly as a linear combination of past p samples 1, 2 up to p if it is p number of sinusoids you can express it as a linear combination of past p samples. That means in this case if you have S_n as a desired response in an optimal filter and you give a delay response s_n , so it is S_n minus 1 then if you have a filter say w_1 dot dot dot w_p and this S_n you give as your desired response then the optimal filter will be like this is your desired response S_n and here you have $w_1 S_n$ minus 1 $w_2 S_n$ minus 2 because current input is S_n delayed so S_n minus 1 w_1 then $w_2 S_n$ minus 2 $w_3 S_n$ minus 3 like $w_1 S_n$ minus 1 $w_2 S_n$ minus 2 up to $w_p S_n$ minus p and we find out these values so that the error variance is minimum then obviously the optimal weights will be w_1 equal to a_1 w_2 equal to a_2 w_p equal to a_p and so these output will be exactly equal to S_n and so filter error output will be 0.

So that means current input is exactly predictable from the past p inputs this is the thing. So I am doing optimal filtering in a linear prediction point of view where current sample is predicted from as a sum of past p samples S_n minus 1, S_n minus 2, S_n minus 1, S_n minus 2, S_n minus p then the corresponding optimal filter coefficients will turn out to be a_1 a_2 a_p because then we see from this expression error can be brought down to 0 therefore your variance can be brought down to 0 which is the minimum if are possible so optimal filter will be this all right this is a beautiful property.

Lecture-20: Application of Adaptive Filter (Contd.)

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Lecture 20

$$r_k(n) = A_k e^{j\omega_k n}$$

$$r_k(n-1) = e^{-j\omega_k n} r_k(n)$$

$$\Rightarrow r_k(n) = e^{j\omega_k n} r_k(n-1)$$

$$\Rightarrow (1 - e^{j\omega_k n} z^{-1}) S_k(z) = 0$$

$$s(n) = \frac{A_1 e^{j\omega_1 n}}{r_1(n)} + \dots + \frac{A_p e^{j\omega_p n}}{r_p(n)}$$

$$(1 - e^{j\omega_{c1} z^{-1}}) S_1(z) = 0$$

$$(1 - e^{j\omega_{c2} z^{-1}}) S_2(z) = 0$$

$$q(z) = (1 - e^{j\omega_{c1} z^{-1}}) \dots (1 - e^{j\omega_{cp} z^{-1}})$$

$$q(z) s(z) = 0 \Rightarrow [1 - a_1 z^{-1} - \dots - a_p z^{-p}] S(z) = 0$$

$$\Rightarrow x(n) = a_1 x(n-1) + a_2 x(n-2) + \dots + a_p x(n-p)$$

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As an example, we can consider we can consider suppose S_n as just some a times cosine some $\omega_c n$ plus ϕ okay. Now this is we can write as \cos is we can write $\cos \theta$ as $\frac{1}{2} e^{j\theta} + \frac{1}{2} e^{-j\theta}$, so it is $\frac{a}{2} e^{j\omega_c n + \phi} + \frac{a}{2} e^{-j\omega_c n + \phi}$. So this is your $S_1(n)$, this is your $S_2(n)$ all right this whole thing this whole thing is your S_2 all right. One frequency ω_c another frequency $\omega_c - \omega_c$. So here the annihilating poly dual will be $e^{j\omega_c n} z^{-1}$ and here frequency is ω_c here minus ω_c so here you get $1 - e^{j\omega_c n} z^{-1}$ because frequency is minus ω_c here okay.

If I take the product of the two this will be my Qz down and this $Qz Sz$ is 0 from my previous discussion all right. But here if I know product if you take the multiplication if you carry out the product 1 into 1 , then you take z inverse common $e^{j\omega_c n} z^{-1}$ and $e^{-j\omega_c n} z^{-1}$ when added that will give you twice cosine $\omega_c z^{-1}$ and then this will cancel $e^{j\omega_c n} z^{-1}$ $e^{-j\omega_c n} z^{-1}$ cancel z inverse 2 okay. So, this is what which means if you now multiply this by $Sz Sz$ into $1 S_n$ that remains on one side other terms you take to the right-hand side

twice minus because plus twice cosine $\omega C z^{-1} S_z$ that is S_n minus 1 and the minus $z^{-2} S_z$ that is S_n minus 2. So A_1 is twice cosine ωC A_2 is minus 1 you can verify yourself you really carry out this sum if you now replace S_n minus 1 by $A \cos(\omega C N - 1 + \phi)$ here and again S_n minus 2 equals to the same thing with N by replace by $N - 2$ okay. Carry out the summation by using trigonometry we will get S_n equal to this you can verify.

We are using DSP Z transform and all that but using pure trigonometry if you replace S_n minus 1 by $A \cos(\omega C N - 1 + \phi)$ and S_n minus 2 by $A \cos(\omega C N - 2 + \phi)$ then do some algebra of trigonometry you will get back summation equal to S_n which is this you can verify all right. So, in this case S_n can be predicted exactly if it is a pure sinusoid, it can be predicted exactly from its past two samples S_n minus 1 S_n minus 2. Ideally one optimal filter coefficient will be $2 \cos \omega C$ another minus 1 okay these are optimal filter or equivalently optimum predictor coefficients prediction coefficients all right. Now we have S_n we have the single X_n which has this S_n but not only S_n some white noise. It is 0 mean white noise independent of that is statistically independent of S_n . So, this is given to me and the noise power is reasonably high so it is not that noise is very small.

Lecture-20: Application of Adaptive Filter (Contd.)

$s(n) = A \cos(\omega_c n + \phi)$
 $= \frac{A}{2} e^{j(\omega_c n + \phi)} + \frac{A}{2} e^{-j(\omega_c n + \phi)}$

$z(n)$: zero-mean white noise independent of $s(n)$

$q(z) = (1 - e^{j\omega_c} z^{-1})(1 - e^{-j\omega_c} z^{-1})$
 $= 1 - 2e^{j\omega_c} z^{-1} + z^{-2}$

$x(n) = s(n) + 2z(n)$

$n(n) = \underbrace{2e^{j\omega_c} n(n-1)}_{a_1 = 2e^{j\omega_c}} - \underbrace{n(n-2)}_{a_2 = -1}$

$q(z)S(z) = 0$

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We can minimize as I told you the very beginning of this course, I will give an example that ideally if you want to eliminate this noise and this is just a cosine sequence so it is in the I know discrete type Fourier transform we will have two impulses one at small omega C another minus omega C. So ideally you should design a band pass filter with very narrow pass band okay one at omega C another minus omega C and pass this sequence Xn through that so this signal Sn will come through the pass band it will go through as it is but almost all of the noise most of the noise will be filtered out by the narrow band filter because it is a white noise so it is present in all frequency ranges thereby the noise will be eliminated when it will large extent to a huge extent actually almost all noise will go except whatever little we have in the pass band or the filter band pass filter. But the problem is if the frequency changes omega C after some time, then the band pass filter will be rejecting this Sn also, because new omega C will be outside the pass band of the band pass filter you designed which has you know pass band around the old omega C. So, it will not work so we have to make it adaptive okay. So, what we do here we give this Xn and we take its delayed version and we pass it through a filter ideally this should be two coefficients but we make it larger does not matter I mean it will be W1 dot dot dot some Wp. This is my

desired response D_n so D_n is S_n okay so here D_n if you are considering an optimal filter what will be W_{opt} here W_{opt} will be what I mean D_n W_{opt} is $R^{-1}p$, R is the auto correlation matrix of the input here okay and p is the cross-correlation vector between the input vector here and D_n . So, p first starts with p , p is expected value of X_{n-1} this vector here means current input is X_{n-1} right, so data vector at $n-1$. So, it will be X_{n-1} vector times D_n now X_{n-1} vector is current sample current bits at $n-1$, then $n-2$ dot dot dot $n-p$, p terms because p coefficients this is X_{n-1} and X_{n-1} what is X_n ? $S_n + Z_n$, so X_{n-1} sample is $S_{n-1} + Z_{n-1}$ X_{n-2} is $S_{n-2} + Z_{n-2}$ like that. So, it will be X that is S actually sorry $S_{n-1} + Z_{n-1}$ let me instead of doing it elaborately let me do one thing let me take a general term here general term means a general term of this vector into D_n say you say X_{n-k} I have got some of X_{n-k} general term so expected value of a particular term X_{n-k} into D_n what happens there? So, $E[X_{n-k} D_n]$ okay what happens to that. Now I know it will be $S_{n-k} + Z_{n-k}$ this X_{n-k} and D_n what is D_n ? D_n is X_n itself which is $S_n + Z_n$. Now this will have one term X_{n-k} into S_n S_{n-k} into S_n that is fine the other cross term is Z_{n-k} S_n the correlation between Z the noise term okay and single term with a gap of k okay. It is N it is $N-k$ but the two terms they are statistically independent and therefore uncorrelated and therefore expected value of the product is product of the expected value of this into this and it is 0 mean so this will go all right because Z and S they are statistically independent in fact that is a strong condition you can even assume they are uncorrelated because statistically independent means uncorrelated. You can even just take it to be uncorrelated only but even in that case the correlation at a gap of k will be you take a product Z_{n-k} into S_n $n-k$ here n here so gap is k now multiply an expected value there is a correlation. If uncorrelated it will be expected value of Z_{n-k} into expected value of S_n which is 0 because each has 0 mean so therefore this cross term goes by the same logic. Expected value of S_{n-k} into Z_n okay this also correlation at a gap $n-k$ this goes and then Z_n with Z_{n-k} now Z_n is Z_n is what Z_n is a white noise white means the sequence where every sample is uncorrelated with every other sample from nearest neighbor to farthest neighbor okay, that is white we have seen earlier.

So Z_n and $n - k$ and k can be 1 2 so whether it is $n - 1$ $n - 2$ $n - 3$ whatever that with Z_n multiplied expected value it will be a correlation autocorrelation of Z_n with itself at a gap of k but Z_n is a white sequence so it is autocorrelation at any k greater than 0 then k can be 1 2 3 anything is 0, because in a white sequence every sample say Z_n will have 0 correlation with its neighbors neighbor can be $n - 1$ so immediate neighbor or $n - 2$ $n - 3$ like that okay so these also goes. So essentially it will be E of n into $S_n - k$ okay. So, but as though as though there is no Z_n you have only S_n so in that case S_n and $S_n - 1$ there is no Z_n okay. If there is no Z_n if you give S_n here, we have seen already if you give S_n here and delay here and $S_n - 1$ $S_n - 2$ then you get the optimal filters such that the error is finally 0 when there is no Z_n . So in this case even when Z_n is present we find that the cross correlation vector p is same as what we would have got if there is no Z_n present because it is just E of S_n into $S_n - k$ okay this is one term so this was just one term now you can carry out with $n - 1$ $n - 2$ $n - k$ minus p . So that means cross correlation term p is E of just $S_n - 1$ vector into S_n itself okay because $n - 1$, $n - 2$, $n - 3$ and all that S_n fixed okay. I took $n - k$ $X_n - k$ arbitrarily could have been $n - 1$ could have been $n - 2$ so general term okay d_n here and now there is no Z present so as though when I compute p for this setup, I get the same p when there is no noise present so just S_n and $S_n - 1$ here and when there is no noise present this predictor coefficients give me an output which is exactly S_n and error is 0 okay. So, for that optimal filter so I mean should have a p vector which is this because that time S_n is the desired response and $S_n - 1$ $S_n - 2$ they are the input terms okay. So, Z_n has no effect on changing the p , p vector cross correlation vector when I have no noise case to a noisy case because there is no Z_n present but changes come here in the autocorrelation matrix.

Autocorrelation matrix is now is of this so E of R is now E of $X_n - 1$ vector $X_n - 1$ right transpose. So, it will have terms like S plus $Z_n - 1$ into X transpose this is what we have now again these been vectors okay

Lecture-20: Application of Adaptive Filter (Contd.)

$s(n) = A \cos(\omega_c n + \phi)$
 $= \frac{A}{2} e^{j(\omega_c n + \phi)} + \frac{A}{2} e^{-j(\omega_c n + \phi)}$

$z(n)$: zero-mean, white noise, independent of $s(n)$

$x(n) = s(n) + z(n)$

$q(z) = (1 - e^{j\omega_c} z^{-1})(1 - e^{-j\omega_c} z^{-1})$
 $= 1 - 2e^{j\omega_c} z^{-1} + z^{-2}$

$a_1 = 2e^{j\omega_c}$ $a_2 = -1$

$p = E \left[\begin{matrix} s(n-1) \\ s(n) \end{matrix} \right]$

$\Phi = E \left[\begin{matrix} x(n-1) \\ d(n) \end{matrix} \right]$

$Q = E \left[\begin{matrix} x(n-1)z^T(n-1) \\ \vdots \\ x(n-1)z^T(n-p) \end{matrix} \right]$

$E \left[x(n-u) d(n) \right] = E \left[(s(n-u) + z(n-u)) (s(n) + z(n)) \right]$

$= E \left[s(n-u)s(n) + z(n-u)z(n) \right]$

Block diagram: $x(n)$ enters a filter block with coefficients w_0, \dots, w_p . The output is $e(n)$. The error signal $d(n)$ is also fed into the filter block. The filter output is summed with $d(n)$ to produce $e(n)$.

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Oh, it is gone so let me go to the next page yeah okay. so, Z_n is the noise vector like X_n minus 1 it has two components S_n minus 1 vector Z_n minus 1 vector that is very simple S_n minus 1 vector means small s_n minus 1, small s_n minus 2, small s_n minus 3 dot dot dot up to S_n minus p Z_n also Z_n vector means Z_n minus 1 vector means Z_n minus 1, Z_n minus 2 dot dot dot Z_n minus p a vector right this is just that. Now S_n minus 1 S_n minus 1 transpose fine no problem it is the correlation of the signal part okay and again because of whites and stationarity n will go it will just be autocorrelation of the input S_n all right. cross terms S_n minus 1 vector and the column vector and another term here is Z_n minus 1 transpose is a row vector. So, every term of some element of S and some element of Z . They are uncorrelated expected value of that will be 0 because they are uncorrelated because they are statistically independent so expected value of some term of this vector is n minus 1 which will be some S_n minus k and some term of this row vector Z_n minus 1 transpose okay that will be this cross term will be 0 because one term consisting of S from here just S_n minus k another may be Z_n minus L okay from here their product and expected value which is a correlation between the two terms which is 0. Again, similarly Z_n minus 1 vector from there if I pick up any elements Z_n minus k because Z_n minus 1 is a column

vector and then S_{n-1} transpose which is a row vector you take any element say maybe S_{n-L} .

So, $Z_{n-k} S_{n-L}$ if you take their product again, they are uncorrelated and therefore 0. So, only other term will be Z_{n-1} and Z_{n-1} transpose that is the autocorrelation matrix of the noise and noise is white, so again it will be a diagonal matrix because their cross-correlation terms of the autocorrelation matrix of Z_{n-1} will be 0. cross terms will be 0 because it is a white sequence only diagonal terms will give the variance okay. So, and because of weights and stationarity of the process all the variances are same they are all dependent on the location okay. So, it will be a constant times identity matrix okay constant times constant that constant is the noise variance for every time index N because it is WSS so that does not change with time index. So, it will be altogether R will be having R let me call it R this thing this is R without noise okay.

So, maybe call it R prime plus some constant σ_N , N for noise σ_N square times identity matrix this is my R and P we have seen it is same as new P same as original okay when there is no noise. So, now, new R inverse P we will have P prime if σ_N square I is very small or it is not present then R inverse P will be same as R prime inverse P prime that is if there is no noise then R inverse P or if the noise power is less very less R inverse will be very close to R prime inverse P , P prime that is which is the optimal filter or the no noise case and that will give me the correct SN and the filter output so that error is 0. But because of the presence of this term there will be you know some deviation from optimality as a result if you have if you have X_N here and then you are passing it through the filter this will be and this is your linear response X_N E_N they will no longer be the original optimal coefficients when there is no noise and therefore, there are no coefficients given by R prime inverse P prime and if you put the coefficients these output is same as X_N so that error is 0. Because if there is no noise, I have got a pure sinusoid which is predictable exactly from its past P samples you have seen. But we do not have just R prime alone we have this extra factor and that is why these filters will no longer be same as that original optimal filter so output here will not be exactly X_N but still close to that X prime N .

So, and these elements the diagonal matrix it only attacks or changes the diagonal elements of R prime which are the variances of the noise input and usually input variance is large. So, only they get perturbed or somewhat modified because of this addition by σ_n^2 square factor other terms are not other terms of R prime they do not get changed. So, what all the change in its effect is not much and therefore, X prime N is close to still XN and error is not ideally 0 now it is not 0 ideally should have been 0 but it is no longer 0 but still close to 0 and in that case, this will be close to XN and XN is the noise free noise XN . Alright and what is X prime N ? X prime N is almost same as I mean the output which you would have got if there is no noise that is X prime N will be close to S N , why S N because if this is not present if the σ_n^2 is not present obviously the output would have been same as S N is not it XN is S N and this is S N minus 1, S N minus 2, S N minus p there you combine them by the optimal coefficient. So, that S N is given exactly by the filter output it is exactly equal to S N at that time your optimal filter coefficient should have been R prime inverse P prime.

Lecture-20: Application of Adaptive Filter (Contd.)

$$R = R' + \sigma_n^2 I$$

$$\phi = \phi'$$

$$R^{-1} \phi = (R' + \sigma_n^2 I)^{-1} \phi'$$

Block diagram showing an adaptive filter structure. The input $x(n)$ is processed by a filter with coefficients w_1, \dots, w_p to produce the output $x'(n)$. The error signal $e(n)$ is calculated as $x(n) - x'(n)$. A note indicates $x'(n) \approx n(n)$.

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R prime is the autocorrelation matrix of S the corresponding cross correlation vector is P

prime. Now there is a change small change caused by the σ_N^2 which is changes the diagonal elements of R prime. As a result, the optimal filter coefficients will no longer be same as original S_N but will be close to S_N because the effect of this may not be much. So, I can be happy with this component okay. I can be happy with this component which will be largely noise free close to original S_N . So, I can be happy with this and now I can make it adaptive because if the frequency changes and all that you know it has to be tracked so I can make it adaptive. This is the filter input adaptive filter and then these coefficients may be by elimination algorithm will be adjusted okay.

So, this is called adaptive line enhancer all right. Remember if the input frequency changes if the input frequency changes correlation also changes okay. As a result, R new R new autocorrelation matrix will be defined from old autocorrelation matrix. You can take one example suppose I give you one signal $S_N A e^{j\omega_c N + \phi}$, this is random because suppose ϕ is random if the phase is random it varies from minus 0 to 2π with some probability okay. In that case the cross correlation suppose ϕ so p_ϕ is given to me suppose I mean ϕ is from this actually you should know ϕ is in this range okay and it within that suppose it is given to me uniform as an example uniform so this is 1 by 2π .

So, 0 to 2π within that probability density is constant so 1 by 2π so 1 by 2π into 2π area is 1 that is what probability density should have if you integrate it should have 1 okay. So, 0 to 2π is where the phase is at that time probability density is constant for all ϕ is called uniform distribution and outside that 0 equal to 0 outside. If this is the case you can verify cross correlation $S_N S_N^*$ if you do then you do you get one term only what S_N is this S_N^* minus k . So, it is but what will come out is just a into this $\omega_c N$ okay minus k and then S_N minus k so basically one term will come out and you will have a square so one term will come out N minus k and otherwise you will have $e^{j\omega_c N + \phi}$ again so it will be twice so s square all right. If you now take the expected value so multiply this by 1 by 2π integrate from 0 to π , so this term will come out okay. This term will come out as it is because it does not have ϕ this term e to the

power $j 2$ is $\omega c N$ plus ϕ this is ϕ . So, if you integrate after multiplying by 1 by 2π and integrate from 0 to 2π this integral will be 0 . Anyway, I think I will consider this I will consider in the next class all right.

Lecture-20: Application of Adaptive Filter (Contd.)

$$R = R' + b_n I$$

$$\underline{p} = \underline{p}' = (R' + b_n I)^{-1} p'$$

$$r(n) = A e^{j(\omega_c n + \phi)}$$

$$r(n) r(n-u) = e^{-j\omega_c u} A^2 e^{j2(\omega_c n + \phi)} \quad 0 \leq u \leq 2\pi$$

$$P_p = \frac{1}{2\pi} \int_0^{2\pi} \dots = 0, \text{ outside}$$

Adaptive Line enhancer ✓

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What I am trying to change this if the input frequency changes cross correlation and autocorrelation values will change so you need a new optimal filter and then that is why this adaptive filter is necessary okay it will track and will move to or you know that adaptive filter you know will take you to the new optimal filter by learning from the input and that is what will happen that thereby it will track the input frequency okay. Let me erase this part if time permits next class, I will just show this but this you can try your hand on with this a very simple textbook exercise okay see you then thank you very much.