

Introduction To Adaptive Signal Processing

Prof. Mrityunjay Chakraborty

Department of Electronics and Electrical Communication Engineering

Indian Institute of Technology, Kharagpur

Lecture No # 27

Second Order Analysis of LMS Algorithm (Contd.)

So, in the last class we had these results. Missed adjustment M was J by $1 - J$, J was summation of i equal to 0 to $N - 1$ $\mu \lambda_i$ by $2 - \mu \lambda_i$. This whole thing is called function J . So, J is a summation of N number of such separate functions ok. We have seen M , M is miss adjustment. So, it is strictly non-negative ok and when it is stable it should be finite.

$$M = \frac{J}{1 - J};$$

$$J = \sum_{i=0}^{N-1} \left(\frac{\mu \lambda_i}{2 - \mu \lambda_i} \right)$$

If we plot M versus G this is what we had obtained. Similar zones we are not interested because to the right of this point J equal to 1, M becomes negative and negative M is of no importance to us ok. Similarly, if you go to the left M becomes negative. So, this is the zone and at J equal to 1 M becomes infinity.

So, at least J equal to 1 and if you put J equal to 1 you solve it, numerator will have a polynomial in μ , denominator will have a polynomial in μ . You solve it with if it is equal to 1, numerator equal to denominator solve it you get a polynomial in μ N th order. So, you get N roots at those values of μ J is 1 and therefore, M does not exist. So, those values of μ are outside the region of convergence ok for the algorithm because if the

algorithm if it converges that is it goes k prime i i N if it goes to finite as N tends to infinity then only it is stable algorithm is stable and if it converges if it leads to finite terms then that summation was I mean M will become this a finite. No other it cannot take any other value.

Lecture-27: Second Order Analysis of LMS Algorithm (Contd.)

Lecture 27

$$M = \frac{J}{1-J}$$

$$J = \sum_{i=0}^{N-1} \left(\frac{\mu \lambda_i}{2 - \mu \lambda_i} \right) \rightarrow J_i$$

$k_{ii}(n) \rightarrow \text{Finite}$
 $n \rightarrow \infty$

Watch later Share

MORE VIDEOS

HP Wolf
Welcome to
Priority

2:57 / 30:15

CC YouTube

So, if it table then the misadjustment takes this value only there is no other value that is possible all right. So, what we did we are plotting J . So, J_0, J_1, J_2 we consider the case where λ is a λ max all λ s are positive because they are corresponding to the eigenvalues of the input autocorrelation matrix which is positive definite. So, if you consider the λ max case see this J_i for any J_i it suits up to infinity only when μ denominated is 0 that is when μ equal to $2 / \lambda_i$ at that value. So, if it is λ max the $2 / \lambda$ max will come first if we start from origin and I am not going to explain again this J versus μ was like this.

So, $2 / \lambda$ max will occur first then again next one maybe $2 / \lambda$ another $2 / \lambda$ by λ max prime that is next to λ max the next value and like this and J equal to 1. So, these are the values of μ by J equal to 1 that is if you solve that polynomial thing ok you get this J equal to 1 and then solve factorize the polynomial and get first order factors. You

understand what I am saying if we equate this to 1 then if you have J_0, J_1, J_2 all these kinds of things you know if you do algebraic addition numerator denominator will be a product of these factors. So, it will be a polynomial in μ , numerator also will be a polynomial μ because $\mu^{\lambda_i} \times 2 - \mu^{\lambda_j} \times 2 - \mu^{\lambda_k}$ like that like that and so on and so forth in other cases. So, numerator will be also a polynomial in μ .

So, numerator by denominator equal to 1, numerator minus denominator 0. So, you have a polynomial equal to 0. So, you factorize the polynomial into first order factors of μ those are the values of μ for which equal it will be left hand side will be equal to 0 means J will be equal to 1 these are those values. Clearly these are the values at which M will suit up to infinity. So, these are outside the region of this thing convergence all right.

After that I did something maybe you know I brought some numbers a, b, c which are between 0 to 1 and I showed one inequality I am coming back to that later. But before that one thing is sure if M is infinity that is j equal to 1 those values of μ cannot be part of the region of convergence that is this figures k prime i i n cannot converge to finite value for those μ because if it at all converges to finite value it will converge to this expression where j is not equal to 1 because j equal to 1 means it if it is it will not converge, converge means converging to finite value or we have seen if it converges it will converge only to those ok this figure with j not equal to 1. So, that is it is a finite value therefore, those μ for which j equal to 1 they will be outside the region of convergence. So, these are the μ 's let me use some other ink. So, this is one μ this is one μ these are the points which lie outside.

Lecture-27: Second Order Analysis of LMS Algorithm (Contd.)

Lecture 27

$M = \frac{J}{1-J}$

$J = \sum_{i=0}^{N-1} \left(\frac{\mu^2 \sigma_i^2}{2 - \mu^2 \sigma_i^2} \right)$

$k'_{ii}(n) \rightarrow \text{Finite}$
 $n \rightarrow \infty$

MORE VIDEOS

6:38 / 30:15

CC YouTube

Now what happens to the intermediate regions between two red dots? If I take that μ does this converge to finite value or not that we do not know, but if it converges to finite value, it will be finite ok it will be finite you will take this expression all right this much. So, I know that at these points this function suits up to infinity. So, $k'_{ii}(n)$ does not converge ok it has to not only converge to M it has to converge to finite M . So, those are the values where this will not converge, but the intermediate range and all I do not know that is because as I told you the other day let me go to a new page. If you take an expression like say suppose $1 + ax + x^2 + \dots$ it gives you a function $f(x)$ equal to 1 by $1 - x$ for this $|x| < 1$ should be less than 1 ok.

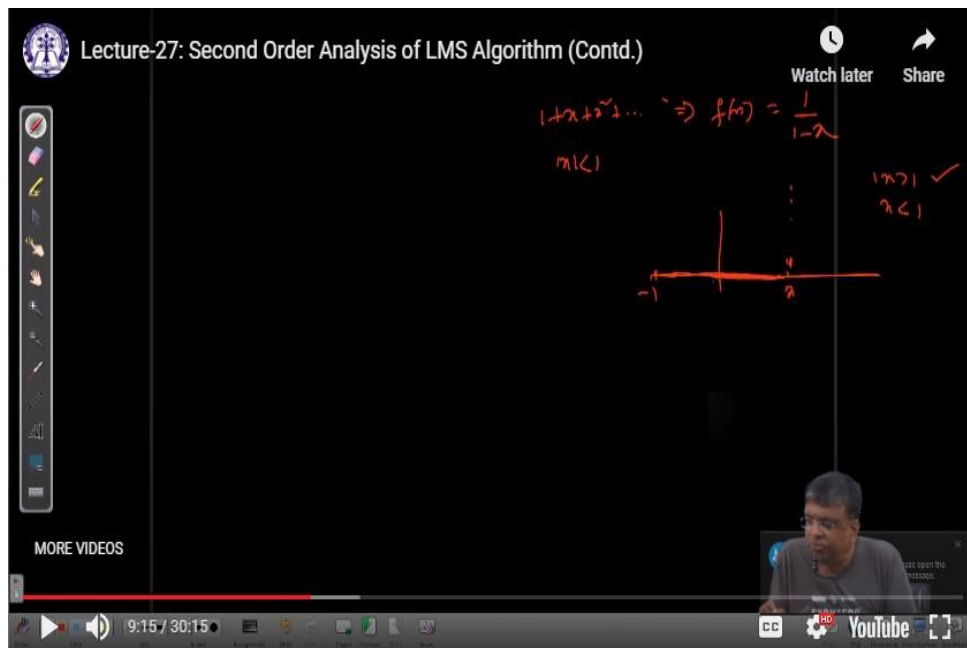
$$1 + x + x^2 + \dots \Rightarrow f(x) = \frac{1}{1 - x}$$

$$|x| < 1$$

So, x equal to 1 so this zone 0 to 1 ok suppose x is positive a real and positive to be less simple. So, 0 to 1 for that region this summation converges to a finite value and if it converges will take this value, but when you look at this function forget about the series

this function does not exist at x equal to 1. So, x equal to 1 cannot be a point of convergence here, because if it is a point of convergence it will converge to this value with a finite value for this functional is a finite value at x equal to 1 that does not happen. So, x equal to 1 cannot be a point of convergence, the point of convergence means this summation will converge to this function with a finite value that is what happening here. So, x equal to 1 is ruled out, but x less than 1 greater than 0 I am assuming x to be say positive otherwise you have to go from minus 1 to 1 if you want to be precise mod x to be less than 1.

So, any of these values here take any of the value this will converge, but when you look at the function, function does not exist at x equal to 1, but it exist at x greater than 1 also at x less than 1 also. Only thing is at x equal to 1 function does not exist means that is not part of the region of convergence of this.



So, this much from the looking at the function this much we can say that the that point where it is should it is does not exist where x equal to 1 that cannot be region of convergence, but the function I know giving the function it exist for x greater than 1 also less than 1 also ok. In fact, it is better if I put it just x greater than 1 alright only it exist only x equal to 1 does not exist. So, from the function by looking at the function I can make

out that it will not converge here ok or here, but function exist on this side also function exist on this side function exist on in this in the region also ok.

Of all these places some zone may be a region of convergence for this series. Now I see one thing if I put x equal to 0 in this series it is 1. So, it is a finite value. So, x equal to 0 is ok it is a region of what are the region of convergence and 0 to 1 is 0 to 1 then what will happen if it converges at a value of x x equal to 0 and then I increase x by very small amount epsilon very small amount ok. It will still be it will not suddenly should up to infinity because epsilon is very small.

So, there is a neighborhood and it will go on like that till we find the point where the summation will finally, should up to infinity its value will be increasing when you give x equal to 0 value is 1 if you give x equal to epsilon may be some positive number value will increase still increase, but finally, at certain value this function will this will this will be shooting up to infinity. So, it will not take this function is a finite value that happens at x equal to 1 before that. So, it will continue to be like this ok going up. So, any this from 0 till we reach here we do not touch this, but in this point, this is convergence ok. So, we find out one point of convergence that is equal to 0 and from that we go to the point of discontinuity point of you know divergence not convergence till that point not touching the point this will converge ok this will converge to this form.

So, this is the thing we bring here. We know that the LMS algorithm w_n plus 1 w_n plus $\mu x_n e_n$. So, w_1 if you take n equal to 0 n equal to 0 w_1 is w_0 and suppose I take μ equal to 0 then this is 0 then w_2 will be w_1 which is again w_0 . So and so because μ is 0 means no updates. So, initial value w_0 continues at w_1 w_2 w_3 .

$$\underline{w}(n + 1) = \underline{w}(n) + \mu \underline{x}(n) e(n)$$

$$w(1) = \underline{w}(0); \quad \mu = 0$$

$$w(2) = w(1) = w(0)$$

So, error error was that component v_n ok, v_n is we know w_n minus w_{opt} , but w_n whether w_n is 1 n is 2 n is 3 it is constant which is w_0 . So, v_n also constant initial value minus w_{opt} .

$$\underline{v}(n) = \underline{w}(n) - \underline{w}_{opt}$$

So, any component of n v_n will be w_n , w_n minus w_{opt} i is constant because w_n is constant i th w_1 is same as w_0 if μ is 0, w_2 is same as w_1 if μ is 0, w_1 is w_0 so on and so forth. So, all the filter weights remain constant at w_0 ok in this case μ equal to 0 case μ equal to 0 then what happens to that error vector weight error vector with respect to the optimal weight. So, w at n th point of time we know it is w_n minus w_{opt} , but w_n does not change it is same as w_0 , w_1 , w_2 , w_3 are all same.

So, that is why v_n also constant if I take any i th component of this vector say v_n it will be i th component of the filter weight vector minus i th component of this and there is a constant because it is not changing with time. So, if that be the variance of this does not change it is finite ok. That means, k_i in less than infinity for all n because variance does not change it is just a constant difference w_n minus w_{opt} i and w_n is nothing, but w_0 because at 0th point of time that initial value whatever I gave w_0 that remains with that remains the case for all n . So, w_0 minus w_{opt} i it is a just finite number it does not change as n changes. So, as a result variance also does not change is a constant variance is just the square of it ok that also remains finite for all n and if it is for k_i in same for same for this is just a transform version of that alright which means μ equal to 0 this always remains finite.

Lecture-27: Second Order Analysis of LMS Algorithm (Contd.)

Lecture 27

$M = \frac{J}{1-J}$

$J = \sum_{i=0}^{N-1} \left(\frac{\mu \lambda_i}{2 - \mu \lambda_i} \right)$

$J_i \rightarrow$

$k_{ii}(n) \rightarrow$ Finite $\mu \rightarrow \infty$

M

$W(n+1) = W(n) + \mu \sum_{i=0}^{N-1} e(n) e_i(n)$

$W(n) = W(n) \Rightarrow \hat{W}(n) = W(n)$

$W(n) = W(n) = W(n) - W_{opt}$

$v_i(n) = W_i(n) - W_{opt,i}$

$\Rightarrow k_{ii}(n) < \infty$ for all n

That means, μ equal to 0 μ equal to 0 this is a point of convergence and not only that we have already seen if μ is much less than 1 by tracer then it is algorithm is stable m remains finite and all that we have seen earlier alright. In fact, you can see μ is much less than 2 by tracer also that will fine,

$$\mu \ll \frac{1}{Tr(R)}$$

But 2 by tracer because 2 by lambda max, we know lambda max is less than sorry it is less than summation of all the eigenvalues right all eigenvalues are positive one of them is lambda max other eigenvalues are also positive. So, summation and that is tracer. So, lambda max less than tracer by r less than tracer. So, 2 by lambda max is greater than 2 by tracer.

So, 2 by lambda max 2 by tracer will be somewhere here. So, if μ is less than this, we have seen already m is finite. So, that means, from μ equal to 0 if you go further to the right we are still in the region of convergence and this will remain so till we hit this point first point where j turns out to be 1 and therefore, m shoots up to infinity. So, at least this

much we can take to be our region of convergence there may be other this place is also possible maybe μ if I take from this region or the some other region maybe it is possible that m also will remain finite for them, but I am not sure, but about this I am sure because μ equal to 0 is a point of stability up to in fact, as long as μ remains much less than 2 by tracer they are all points of stability and therefore, I can go up to I can increase, increase, increase till the point I time I hit this point where m shoots up to infinity because j touches 1 all right. So, I will be just finding out this range that means, I will find out at what point this will become 1 let me draw again.

So, these are the points these are the points ok let me draw again this by j this by μ and j will shoot up to infinity at 2 by λ_{max} then next time 2 by λ_{max} maybe like that. So, this will be like this next one again next one like this j equal to 1 is the case at point. So, this is this fellow this fellow these are the points of discontinuity, but I have seen at least one thing if I remain to the left from 0 to this till I hit this point because this μ equal to 0 is a point of stability and then if I go further to the right at least as long as μ remains much less than 2 by tracer m this is stable because m remains finite and if I go further and further this increases till we hit this point. So, this will be at least a guaranteed region of convergence in μ there may be other places also ok there may be other places

also like from here if I go up to the next point maybe here also it is fine if I take μ from here m will be finite, but I am not sure I cannot work that out that is very difficult math very tedious, but I can work for this part there at this μ from here to here if I take μ from here to here I will be within the region of stability where μ equal to 0 is a point of stability and as you go along till 2 by tracer stability and you can extend further till it becomes μ equal to this point for which j is 1 alright. That means you have to equate that j equal to 1 and find it out what are the values of μ for which j equal to 1 take the 1 which is smallest, but that is again very tedious ok that is why we will not be using this I will do some further I would say approximation I will apply further tricks we have seen already that if a, b, c they are between 1 to 0.

So, that $a + b + c$ also between 1 to 0 which means a plus they are positive. So, that means $a + b$ is between 1 to 0 $a + c$ between 1 to 0 $a + c$ between 1 to 0 then a by $1 - a + b$ by $1 - b + c$ by $1 - c$ is also less than $a + b + c$ by $1 - a + b + c$. In fact, you can generalize suppose $a_1 a_2 \dots a_n$ maybe $a_0 a_1$ sorry there are some constants between 0 to 1. So, that $a_0 + a_1 + \dots + a_n - 1$ is between these then we can extend this a_0 by $1 - a_0 a_1$ by $1 - a_1 + \dots + a_n - 1$ by $1 -$ this is less than summation of these terms $a + b + c$ now it is summation a_i by $1 -$ the same summation right. Now, we are doing this what is the expression of J ? J_i is $\mu \lambda_i$ by $2 - \mu \lambda_i$.

Lecture-27: Second Order Analysis of LMS Algorithm (Contd.)

$0 < a, b, c < 1$
 $0 < a+b+c < 1$
 $\frac{a}{1-a} + \frac{b}{1-b} + \frac{c}{1-c} < \frac{a+b+c}{1-(a+b+c)}$
 $\Rightarrow 0 < a_0, a_1, \dots, a_{N-1} < 1$
 $0 < a_0 + a_1 + \dots + a_{N-1} < 1$

$\frac{a_0}{1-a_0} + \frac{a_1}{1-a_1} + \dots + \frac{a_{N-1}}{1-a_{N-1}} < \frac{\sum_{i=0}^{N-1} a_i}{1 - \sum_{i=0}^{N-1} a_i}$

Watch later Share

MORE VIDEOS

21:56 / 30:15

YouTube

So, you take two common it is half mu lambda i by 1 minus that is we have got this was J0 then right. We have seen mu should be less than 2 by tracer we transform the convergence in mean condition right that means, what is tracer? Summation of the eigenvalues. So, mu into tracer should be less than 2 or half that means, half if you take 2 here 1 by 2 half mu into tracer tracer means lambda 0 plus lambda 1 should be less than 1 and of course, greater than 0. So, mu is greater than 0 tracer is greater than 0, but what does it mean? Half mu lambda 0 plus half mu lambda 1 half mu lambda 0 half mu lambda 1 they are summation less than 1 ok and they are in the visual also they are between 1 to 0 ok. Because when you take all the eigenvalues then half mu and summation of the eigenvalue it is less than 1 if you take only one eigenvalue and all are positive then obviously, half mu lambda 0 less than 1 half mu lambda 1 less than 1 half mu lambda 2 less than 1 and like that.

So, these two ok maybe I can take one more term here. If I take these two terms if we call this A numerator A A by 1 minus A plus B by 1 minus B A is definitely between 1 to 0 A is half mu lambda 0 because with half mu and all the eigenvalues summed and all are positive eigenvalues if that is less than 1. So, if you have only one eigenvalue or two eigenvalue multiplied by mu and half that is obviously, between 1 to 0. So, this is between

1 to 0 if you call it A A by 1 minus A and B by 1 minus B. So, this part will be less than A plus B by 1 minus A plus B.

Then again A plus B means half mu within bracket lambda 0 plus lambda 1. Again, if you take half mu just lambda 0 plus lambda 1 only remember other eigenvalues. Obviously, it will still be less than 1 greater than 0 because with all eigenvalues which are positive added it is still less than 1. So, if you take just two of them obviously, it will be less than 1. So, half mu bracket lambda 0 plus lambda 1 if you call it B.

So, D by 1 minus D, D is also between 1 to 0 and this guy D is also between 1 to 0 and their summation half mu lambda 0 plus lambda 1 plus lambda 2 that is also between 1 to 0. So, that will be this will be less than D plus if you call it C D plus C by 1 minus D plus C and go on doing it. So, then we finally, that is half mu trace of R because summation of eigenvalue is same as trace of the autocorrelation matrix that is what I have used here ok. So, let me call it a function of mu. So, this function is above j for any value of mu j is less than f of mu.

Lecture-27: Second Order Analysis of LMS Algorithm (Contd.)

Watch later Share

$$J_i = \frac{\mu^2 \lambda_i}{2 - \mu \lambda_i} = \frac{\frac{1}{2} \mu \lambda_i}{1 - \frac{1}{2} \mu \lambda_i}$$

$$J = \frac{\frac{1}{2} \mu \lambda_0}{1 - \frac{1}{2} \mu \lambda_0} + \frac{\frac{1}{2} \mu \lambda_1}{1 - \frac{1}{2} \mu \lambda_1} + \frac{\frac{1}{2} \mu \lambda_2}{1 - \frac{1}{2} \mu \lambda_2} + \dots + \frac{\frac{1}{2} \mu \lambda_{N-1}}{1 - \frac{1}{2} \mu \lambda_{N-1}}$$

$$\leq \frac{\frac{1}{2} \mu (\lambda_0 + \lambda_1 + \dots + \lambda_{N-1})}{1 - \frac{1}{2} (\lambda_0 + \lambda_1 + \dots + \lambda_{N-1})}$$

$$= \frac{\frac{1}{2} \mu \text{Tr}\{R\}}{1 - \frac{1}{2} \text{Tr}\{R\}} = f(\mu)$$

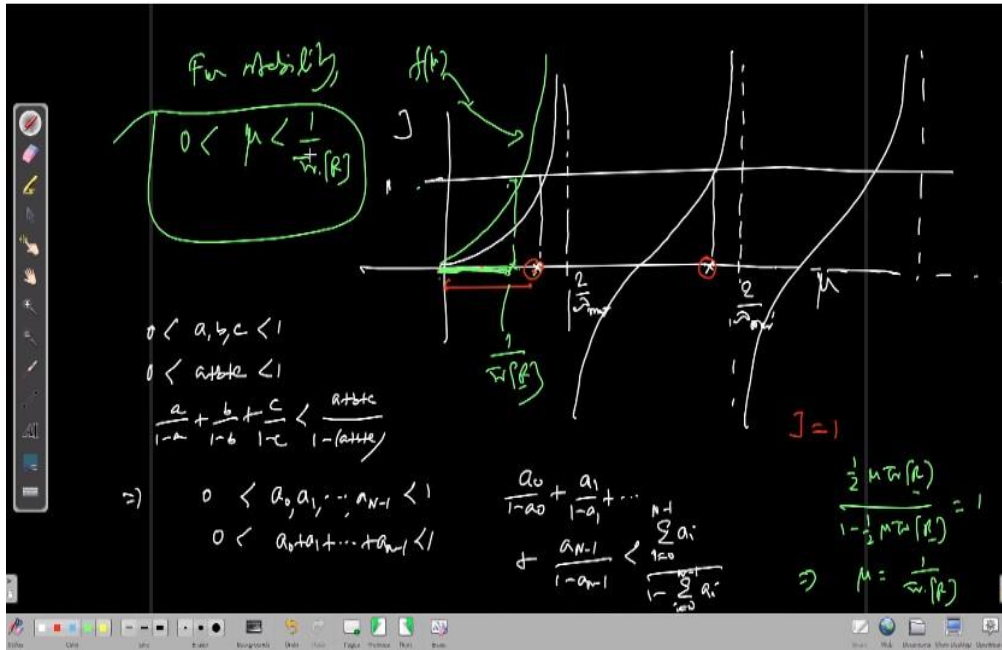
$0 < \mu < \frac{2}{\text{Tr}\{R\}} \Rightarrow \frac{1}{2} \mu (\lambda_0 + \lambda_1 + \dots + \lambda_{N-1}) < 1$

MORE VIDEOS

26:50 / 30:15 CC YouTube

That means, if I plot f of μ it will at any value of μ it will be above this. So, it might be like this f of μ because at any point of μ f of μ will be above this which means it will cut this a equal to 1 line earlier here before this point and there is within the region of stability this much there is to the left of this point of instability or divergence there is non convergence this point is to the left of this. So, now, what I will do I will take only this segment as my region of stability I know some points to the right will be missing, but I cannot find them at least this much if I take I will guaranteed that μ will not suit up to infinity and therefore, algorithm will be stable you know that x is mean square error variance will not go up all that. So, what is this point? This point is when f of μ this curve equal to 1 and f of μ was what was f of μ half μ trace R by half μ trace R if that is equal to 1. So, you take to the then this will basically μ equal to 1 by tracer.

So, this point is alright 1 by tracer. So, for convergence for stability we need μ less than 1 by tracer this zone. Alright if you choose μ here your algorithm will be stable μ will be under control ok we will find n value. So, the excess mean square error variance will not suit up to infinity.



So, I stop here today we have done enough analysis of the LMSI algorithm both first order and second order this convergence in mean and that weight error correlation matrix or covariance matrix or variance of that whether it suits up to infinity or not output mean square error you know and it is a square mean or that rather excess mean square error normalized which is misadjustment in the steady state whether that remains finite or not all these things we have analyzed. I did not give proof of some other results because that is beyond us now given the paucity of time, but with this you can work out this is your region of stability alright.

So, this much for today and I will join you next time. Thank you very much.