

**Introduction To Adaptive Signal Processing**  
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**Lecture No # 39**

**Derivation of the RLS transversal adaptive filter**

So, we will be deriving this recursively squares algorithm. So, we have already defined and seen these things actually  $x(n)$  can be partitioned like this. This was where sorry ok. There was one partition another is  $d(n)$  as we know it was  $d(n-1)$  then  $d(n)$ . So, this part you can write as  $d$  vector with  $n$  replaced by  $n-1$  and then current component  $d(n)$ .

$$\underline{X}_n = \begin{bmatrix} \underline{X}_{n-1} \\ \underline{x}^t(n) \end{bmatrix} \text{ where } \underline{x}(n) = \begin{bmatrix} x(n) \\ x(n-1) \\ \vdots \\ x(n-N+1) \end{bmatrix}$$

$$\underline{d}(n) = \begin{bmatrix} d(0) \\ \vdots \\ d(n-1) \\ d(n) \end{bmatrix} = \begin{bmatrix} \underline{d}(n-1) \\ d(n) \end{bmatrix}$$

Another one  $\lambda^n$  it was  $\lambda$  to the power  $n$  this we can write as this is 0 as though this is 0 vector its transpose this much this is 0 column vector this is this 1 ok. So, I am basically partitioning last row is this of which I have all 0s here and just a 1 and last column all 0s here this 1. So, this upper half  $\lambda$   $\lambda^2$   $\lambda^3$  to the power  $\lambda^n$ . So,  $\lambda$  you can take common.

So, it will be 1  $\lambda$   $\lambda^2$  this will be  $\lambda$  to the power  $n-2$  because 1  $\lambda$  has been taken out this will be  $\lambda$  to the power  $n-1$ . So, that will be this matrix at  $n-1$  this is important. What is this at  $n-1$ ? It will be 1  $\lambda$

lambda square dot dot lambda to the power n minus 2 lambda to the power n minus 1 because this index is n minus 1 that is what I have. If I take out this 1 here all of them have lambda common if I take lambda out then this will be 1 then lambda lambda square this will be lambda to the power n minus 2 lambda to the power n minus 1 ok. So, this sub matrix will be this lambda n minus 1 sub matrix 1 lambda has been taken out as common.

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$$\underline{w}_n = (\underline{X}_n^t \underline{\Lambda}_n \underline{X}_n)^{-1} \underline{X}_n^t \underline{\Lambda}_n \underline{d}(n)$$

where  $\underline{X}_n = \begin{bmatrix} \underline{X}_{n-1}^t \\ 1 \end{bmatrix}$

where  $\underline{\Lambda}_n = \begin{bmatrix} \underline{\Lambda}_{n-1} & 0 \\ 0 & 1 \end{bmatrix}$

$\underline{d}(n) = \begin{bmatrix} d(n-1) \\ d(n) \end{bmatrix}$

So, this is what this we will be using and what we will be going for we know W this is what we have to calculate from Wn minus 1 recursively not by using the formula, but Wn minus 1 also likewise given by something like this all right. So, from Wn minus 1 we must generate the Wn recursively by simple update equation ok. Up till n minus 1 I had only Xn minus 1 data matrix Dn minus 1 data vector and this was lambda n minus 1 matrix ok. At nth clock new data has come X of n using that I build up this Xn and add a row. Similarly new Dn minus 1 has come so add this extra element at the bottom and this matrix enlarges to this ok.

$$\underline{w}_n = (\underline{X}_n^t \underline{\Lambda}_n \underline{X}_n)^{-1} \underline{X}_n^t \underline{\Lambda}_n \underline{d}(n)$$

$$\underline{w}_{n-1} = (\underline{X}_{n-1}^t \underline{\Lambda}_{n-1} \underline{X}_{n-1})^{-1} \underline{X}_{n-1}^t \underline{\Lambda}_{n-1} \underline{d}(n-1)$$

Using this additional information  $W_n$  is to be calculated, but not by this formula, but directly from  $W_{n-1}$  because there are too many things common between  $W_n$  and  $W_{n-1}$  that is these matrices  $X_n$  to  $X_{n-1}$  ok this much is common  $X_{n-1}$  is common  $D_n$  and  $D_{n-1}$   $D_{n-1}$  part is common and likewise this part we have to do. And of course, we are assuming both  $X_n$   $X_{n-1}$  full rank if there is invertible full rank so that this is invertible ok. Let me call this product  $A_n$  so this will be  $A_{n-1}$ . So, I am assuming  $A_n$  and  $A_{n-1}$  both are invertible  $A_n$  is ok this is my  $A_n$ ,  $A_{n-1}$  is just replace  $n$  by  $n-1$   $n$  by  $n-1$   $n-1$  and both cases inverse is coming. So, I am assuming that they are all invertible that is small  $n$  time index is at least equal to capital  $N$  or more ok not before that.

$$\underline{A}_n = \underline{X}_n^t \underline{\Lambda}_n \underline{X}_n$$

$$\underline{A}_{n-1} = \underline{X}_{n-1}^t \underline{\Lambda}_{n-1} \underline{X}_{n-1}$$

What happens before that that we see later I have to take care of that that we will see later. So, this is my  $A_n$ . So, a actually  $W_n$  is  $A_n$  inverse say this part.

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$$\underline{w}_{n-1} = \left( \underline{x}_{n-1}^t \underline{\Lambda}_{n-1} \underline{x}_{n-1} \right)^{-1} \underline{x}_{n-1}^t \underline{\Lambda}_{n-1} \underline{d}(n-1)$$

$$\underline{w}_n = \left( \underline{x}_n^t \underline{\Lambda}_n \underline{x}_n \right)^{-1} \underline{x}_n^t \underline{\Lambda}_n \underline{d}(n)$$

(Assuming both  $\underline{x}_n, \underline{x}_{n-1}$  : full rank)

$$\underline{A}_n = \underline{x}_n^t \underline{\Lambda}_n \underline{x}_n$$

$$\underline{x}_n = \begin{bmatrix} \underline{x}_{n-1} \\ \underline{x}(n) \end{bmatrix}, \text{ where } \underline{x}(n) = \begin{bmatrix} x(n) \\ x(n-1) \\ \vdots \\ x(n-N+1) \end{bmatrix}$$

$$\underline{d}(n) = \begin{bmatrix} d(n) \\ d(n-1) \\ \vdots \\ d(n) \end{bmatrix} = \begin{bmatrix} \underline{d}(n-1) \\ \underline{d}(n) \end{bmatrix}$$

$$\underline{\Lambda}_n = \begin{bmatrix} \underline{\Lambda}_{n-1} & \underline{0} \\ \underline{0} & \underline{1} \end{bmatrix} = \begin{bmatrix} \underline{\Lambda}_{n-1} & \underline{0} \\ \underline{0} & 1 \end{bmatrix}$$

So,  $\underline{A}_n$  so what is  $\underline{W}_n$  is  $\underline{A}_n$  inverse  $\underline{D}_n$  right. Now what is  $\underline{A}_n$ ?  $\underline{A}_n$  was  $\underline{X}_n$  transpose.

$$\underline{w}_n = \underline{A}_n^{-1} \underline{X}_n^t \underline{\Lambda}_n \underline{d}(n)$$

$$\underline{A}_n = \underline{X}_n^t \underline{\Lambda}_n \underline{X}_n$$

So, let us first do this part  $\underline{X}_n$  you remember was  $\underline{X}_n$  minus 1 it was partitioned like this and this was it was done in the previous page. So, no need to explain again. So, if I carry out this part this into this. So,  $\underline{X}_n$  transpose this is  $\underline{X}_n$   $\underline{X}_n$  transpose means first row becomes first column second row becomes second column like that and this last row becomes last column. So, it will be first row of  $\underline{X}_n$  minus 1 is first column here first column here second row of  $\underline{X}_n$  minus 1 second column here dot dot dot ok.

And last row will be last column say  $\underline{X}$  transpose  $n$  is a row vector its transpose you know this will  $\underline{X}_n$  this will come here alright  $\underline{X}$  transpose  $n$  is this row. So, when you make a column of it you have to take a transpose of that that is what  $\underline{X}_n$ . So, this is  $\underline{X}_n$  transpose and  $\underline{d}_n$  I am reproducing here again and we had just seen that block wise partitioning

of matrices and their multiplication. So, this will be this matrix times. So, first I consider this part.

So, this matrix times this plus this matrix which is the vector times this. So, this will be this matrix term this means lambda is a scalar. So, lambda I can take in the front then this matrix times this plus  $X_n$  into 0  $X_n$  is a column vector 0 transpose is a row vector. So, column every element this column into a 0 will give a 0. So, it will be a all 0 matrix  $X_n$  is a column vector 0 transpose is a all 0 vector row vector when you multiply you get a 0 matrix with all elements 0 very simple.

So, that when added with this contributes nothing. So, I am not adding that and then this matrix times 0 column vector which is 0 plus this column vector times 1 which is  $X_n$ . So, it will be  $X_n$ . So, this much then I have this product times  $X_n$ . So, this times this times  $X_n$  and  $X_n$  is equal to 0.

$$\begin{aligned} \underline{W}_n &= \underline{A}_n^{-1} \underline{X}_n^T \underline{\lambda}_n d(n) ; \\ \underline{A}_n &= \underline{X}_n^T \underline{\lambda}_n \underline{X}_n \\ \underline{X}_n^T \underline{\lambda}_n &= \left[ \begin{array}{c|c} \underline{X}_{n-1}^T & \underline{\lambda}_n \end{array} \right] \left[ \begin{array}{c|c} \underline{\lambda}_{n-1} & 0 \\ \hline 0^T & 1 \end{array} \right] \\ &= \left[ \underline{\lambda}_{n-1}^T \underline{X}_{n-1} \quad \underline{\lambda}_n \right] \end{aligned}$$

$$\underline{X}_n = \begin{bmatrix} X_{n1} \\ \vdots \\ X_{ni(n)} \end{bmatrix}$$

$$\underline{\lambda}_n = \left[ \begin{array}{c|c} \underline{\lambda}_{n-1} & 0 \\ \hline 0^T & 1 \end{array} \right]$$

So, this is the product times  $X_n$ . So, I use this partition again. So, that means, this sub

matrix times  $X_n$  minus 1 plus this sub matrix which is column vector times  $X$  transpose  $n$ . So, it will be  $\lambda$  plus  $X_n$  minus 1 and what is this part? By definition this entire thing is a  $n$  minus 1, a  $n$  when  $X_n$  transpose  $\lambda$   $X_n$  a  $n$  minus 1  $X_n$  minus 1 transpose  $\lambda$   $n$  minus 1  $X_n$  minus 1. So, this actually  $\lambda$  times a  $n$  minus 1 plus this extra component.

This is very interesting this shows how a  $n$  we started with a  $n$  how a  $n$  comes from a  $n$  minus 1. This is your a  $n$ , a  $n$  comes from a  $n$  minus 1. This  $\lambda$  times  $n$  minus 1 plus an extra term. What is the extra term? Current input vector into  $X$  transpose a very simple thing, but I am actually interested in inverse of a  $n$ . So, I will have to take inverse of a  $n$  that is inverse of right-hand side and here I will be using that matrix inversion lemma.

Handwritten mathematical derivation on a blackboard background:

$$\underline{w}_n = \underline{A}_n^{-1} \underline{x}_n^t \underline{\lambda}_n d(n);$$

$$\underline{A}_n = \underline{x}_n^t \underline{\lambda}_n \underline{x}_n$$

$$\underline{x}_n^t \underline{\lambda}_n = \left[ \underline{x}_{n-1}^t : \underline{x}(n) \right] \left[ \begin{array}{c|c} \underline{\lambda}_{n-1} & \underline{0} \\ \hline \underline{0}^t & 1 \end{array} \right]$$

$$= \left[ \underline{\lambda}_{n-1}^t \underline{x}_{n-1} : \underline{x}(n) \right];$$

$$\underline{A}_n = (\underline{x}_n^t \underline{\lambda}_n) \underline{x}_n = \left[ \underline{\lambda}_{n-1}^t \underline{x}_{n-1} : \underline{x}(n) \right] \begin{bmatrix} \underline{x}_{n-1} \\ \underline{x}^t(n) \end{bmatrix} = \underline{\lambda}_{n-1}^t \underline{x}_{n-1} \underline{x}_{n-1} + \underline{x}(n) \underline{x}^t(n)$$

Annotations in green:

- $\underline{\lambda}_{n-1}$  is labeled  $\underline{A}_{n-1}$
- $\underline{x}_{n-1} \underline{x}_{n-1}^t$  is labeled  $\underline{A}_{n-1}$
- The final result is labeled  $\underline{\lambda}_{n-1} + \underline{x}(n) \underline{x}^t(n)$

So, again I go here you remember matrix inversion lemma was this for your sake I am writing once again assuming a to be invertible and this also invertible. So, it was this times this is what we have derived and now we have got with the properties of the previous page a  $n$  equal to  $\lambda$   $n$  minus 1 plus  $X_n X$  transpose  $n$  all right. That is I have a  $n$  equal to  $\lambda$  times a  $n$  minus 1 plus again let us see  $\lambda$  times a  $n$  minus 1 plus  $X_n X$

transpose  $n$ . So, this is what we have derived. So, this is what we have derived, but I am interested in  $A_n^{-1}$  I am assuming both  $A_n$  and  $A_{n-1}$  they are invertible.

$$\underline{A}_n = \lambda \underline{A}_{n-1} + \underline{x}(n) \underline{x}^t(n)$$

This is invertible that the total is invertible that is what I am assuming all right. So,  $A_n^{-1}$  then will be if I take  $\lambda$  out I take  $\lambda$  common out plus  $\lambda$  inverse of  $\lambda$  times  $\lambda$   $n-1$  plus  $X_n X$   $\lambda$  inverse  $\lambda$  is not 0 it is between 0 to 1. So,  $\lambda$  inverse no problem. So, this is like your  $A$  this one  $\alpha$  is  $\lambda$  inverse  $\alpha$  is  $X_n$  and you have to invert. So, when you apply  $A_n^{-1}$   $\lambda$  also becomes  $\lambda$  inverse  $\lambda$  inverse because  $\lambda$  also is a matrix 1 by 1 matrix  $\lambda$  inverse which then you write a scalar  $\lambda$  inverse and then put anywhere as in the beginning and the end and inverse of this apply the lemma here inverse minus  $\lambda$  inverse is  $\alpha$  by 1 plus  $X_n X_n X_n X_n X_n X_n X_n X_n X_n X_n X_n X_n X_n X_n X_n X_n$ .

$$\underline{A}_n = \lambda [A_{n-1} + \lambda^{-1} \underline{x}(n) \underline{x}^t(n)]$$

So, this is a transpose again  $\lambda$  inverse  $\alpha$  is  $X_n$ . So, a transpose that is  $X$  transpose  $n$ ,  $\alpha$  is a  $n-1$  inverse  $\alpha$  inverse  $\alpha$  is a  $n-1$  here and again small  $\alpha$  small  $\alpha$  is  $X_n$  this much into this. So, this is a inverse  $\alpha$  is  $X_n X_n X_n X_n X_n X_n$ . So, this is a  $n-1$  here inverse  $X_n$  is  $\alpha$  and now bring  $\lambda$  inverse inside because  $\lambda$  inverse  $\lambda$  to the power minus 2. So, let me take this to be this remember this matrix is a column vector.

$$= \lambda^{-1} \left[ \underline{A}_{n-1}^{-1} - \frac{\lambda^{-1}}{1 + \lambda^{-1} \underline{x}^t(n) \underline{A}_{n-1}^{-1} \underline{x}(n)} \underline{A}_{n-1}^{-1} \underline{x}(n) \underline{x}^t(n) \underline{A}_{n-1}^{-1} \right]$$

So, matrix into column vector is a column vector is a row vector row into column is scalar. So, let me give this scalar a name  $\beta_n$ . So, notational it will be easier all right. So, it is  $\lambda$  inverse into this minus  $\lambda$  to the power minus 2 by 1 plus  $\beta_n$  times this thing this one relation you have found out.

$$= \lambda^{-1} \underline{A}_{n-1}^{-1} - \frac{\lambda^{-2}}{1 + \lambda^{-1} \underline{x}^t(n) \underline{A}_{n-1}^{-1} \underline{x}(n)} \underline{A}_{n-1}^{-1} \underline{x}(n) \underline{x}^t(n) \underline{A}_{n-1}^{-1}$$

The image shows a handwritten derivation of the Kalman gain formula on a blackboard. The equations are as follows:

$$\begin{aligned} (\underline{A} + \alpha \underline{x} \underline{x}^t)^{-1} &= \underline{A}^{-1} - \frac{\alpha}{1 + \alpha \underline{x}^t \underline{A}^{-1} \underline{x}} \underline{A}^{-1} \underline{x} \underline{x}^t \underline{A}^{-1} \\ \underline{A}_n &= \beta \underline{A}_{n-1} + \underline{x}(n) \underline{x}^t(n) = \beta \left[ \underline{A}_{n-1} + \beta^{-1} \underline{x}(n) \underline{x}^t(n) \right] \\ \underline{A}_n^{-1} &= \beta^{-1} \left[ \underline{A}_{n-1} + \beta^{-1} \underline{x}(n) \underline{x}^t(n) \right]^{-1} \\ &= \beta^{-1} \left[ \underline{A}_{n-1}^{-1} - \frac{\beta^{-1}}{1 + \beta^{-1} \underline{x}^t(n) \underline{A}_{n-1}^{-1} \underline{x}(n)} \underline{A}_{n-1}^{-1} \underline{x}(n) \underline{x}^t(n) \underline{A}_{n-1}^{-1} \right] \\ &= \beta^{-1} \underline{A}_{n-1}^{-1} - \frac{\beta^{-2}}{1 + \beta^{-1} \underline{x}^t(n) \underline{A}_{n-1}^{-1} \underline{x}(n)} \underline{A}_{n-1}^{-1} \underline{x}(n) \underline{x}^t(n) \underline{A}_{n-1}^{-1} \end{aligned}$$

The final term in the last equation is labeled  $\beta_n$  with an arrow pointing to it.

Then for some you know algebraic covariance if I consider this a  $n$  inverse multiplying  $X_n$  then what happens if this a  $n$  inverse works on  $X_n$  that means right hand side working on  $X_n$  that means this working on  $X_n$  minus this lambda to the power minus 2 by 1 plus beta  $n$  times this thing into after this there is a  $X_n X_n$  all right.

This was already there these four terms these four terms after that  $X_n$ , but then the advantage is I can put a bracket around this and this is nothing, but again beta  $n$   $X$  transpose  $n$  a  $n$  minus 1 inverse  $X_n$ . So, this is again beta  $n$ . So, then life becomes simple it is lambda inverse a  $n$  minus 1 inverse  $X_n$  minus lambda to the power minus 2 divided by 1 plus lambda inverse beta  $n$  into beta  $n$  scalar you can write first and then a  $n$  minus 1 inverse  $X_n$  okay.



$$\begin{aligned}
 (A + \alpha \underline{x} \underline{x}^t)^{-1} &= A^{-1} - \frac{\alpha}{1 + \alpha \underline{x}^t A^{-1} \underline{x}} A^{-1} \underline{x} \underline{x}^t A^{-1} \\
 \underline{A}_n &= \lambda \underline{A}_{n-1} + \underline{x}(n) \underline{x}^t(n) = \lambda \left[ \underline{A}_{n-1} + \lambda^{-1} \underline{x}(n) \underline{x}^t(n) \right] \\
 \underline{A}_n^{-1} &= \lambda^{-1} \left[ \underline{A}_{n-1} + \lambda^{-1} \underline{x}(n) \underline{x}^t(n) \right]^{-1} \\
 &= \lambda^{-1} \left[ \underline{A}_{n-1}^{-1} - \frac{\lambda^{-1}}{1 + \lambda^{-1} \underline{x}^t(n) \underline{A}_{n-1}^{-1} \underline{x}(n)} \underline{A}_{n-1}^{-1} \underline{x}(n) \underline{x}^t(n) \underline{A}_{n-1}^{-1} \right] \\
 &= \lambda^{-1} \underline{A}_{n-1}^{-1} - \frac{\lambda^{-2}}{1 + \lambda^{-1} \underline{x}^t(n) \underline{A}_{n-1}^{-1} \underline{x}(n)} \underline{A}_{n-1}^{-1} \underline{x}(n) \underline{x}^t(n) \underline{A}_{n-1}^{-1} \\
 \underline{A}_n^{-1} \underline{x}(n) &= \lambda^{-1} \underline{A}_{n-1}^{-1} \underline{x}(n) - \frac{\lambda^{-2}}{1 + \lambda^{-1} \beta_n} \underline{A}_{n-1}^{-1} \underline{x}(n) \underbrace{\left( \underline{x}^t(n) \underline{A}_{n-1}^{-1} \underline{x}(n) \right)}_{\beta_n}
 \end{aligned}$$

Let me write down again this means if I carry out this product I have from previous page see first I find out a n inverse formula then I am just carrying out one result if I use a n inverse a n inverse times  $\underline{x}_n$  what will happen now because I know the a n inverse formula. So, I replace a n inverse by this what happens to that I will require that later that is I am working out.

So, it will be  $\lambda^{-1}$  then a n inverse  $\underline{x}_n$  minus  $\lambda^{-2}$  by  $1 + \lambda^{-1} \beta_n$  times this quantity this  $\beta_n$  I write first this is a scalar I can write in the front or in the end does not matter. So,  $\beta_n$  and then this this fellow is a matrix into column vector this is common matrix into vector matrix common this is scalar this is scalar. So, I can just take  $\lambda^{-1}$  here minus  $\lambda^{-2}$  by  $\beta_n$  divided by  $1 + \lambda^{-1} \beta_n$  these are whole scalar thing multiplying this matrix times  $\underline{x}_n$  and here you see 1 into  $\lambda^{-1}$  that remains  $\lambda^{-1}$   $\lambda^{-1} \lambda^{-2} \beta_n$  that cancels with this. So, what you get is  $\lambda^{-1}$  by  $1 + \lambda^{-1} \beta_n$  and what was  $\beta_n$  now you can replace  $\beta_n$  by this thing, this is scalar times this quantity and this entire quantity right hand side let me call it a vector  $\underline{G}_n$  approximately vector matrix times a column vector that is what

it is this is scalar matrix into column vector. So, vector I call it a gain vector this is one important result.

So, what I have done here is now I know  $G_n$  and I know what is this  $A_n$  inverse I can write this right hand side using  $G_n$  to make it look simpler. So, to do that first let me write down what was my  $A_n$  inverse originally obtained  $\lambda$  inverse  $A_n$  minus 1 inverse minus this is the original form  $\lambda$  to the power minus 2 like this into this. This is what we have obtained earlier now this look at this part  $\lambda$  to the power minus 2 take one  $\lambda$  inverse out. So,  $\lambda$  inverse  $\lambda$  inverse 1 plus  $\lambda$  inverse  $\times$  transpose  $A_n$   $A_n$  minus 1 inverse  $\times n$  same thing here and  $A_n$  minus 1 inverse  $\times n$   $A_n$  minus 1 inverse  $\times n$ . So, this part if I take if I write like this into  $\lambda$  inverse.

So, this entire part  $\lambda$  inverse by this into this this much this much this is nothing, but my  $G_n$  look at  $G_n$   $\lambda$  inverse  $\lambda$  inverse 1 plus 1 plus  $\lambda$  inverse and all these things  $A_n$  minus 1 inverse  $\times n$  this  $G_n$ . So, that means, these are the interesting result this is the  $\lambda$  inverse  $G_n$  and this thing. So, not only  $A_n$  comes from  $A_n$  minus 1 now  $A_n$  inverse also come from  $A_n$  minus 1 inverse through this relation there is an extra term this is the most important thing because in that formula it is not  $A_n$ ,  $A_n$  inverse comes. So,  $W_n$  has  $A_n$  inverse  $W_n$  minus 1 has  $A_n$  minus 1 inverse. So, I have to relate  $A_n$  inverse with  $A_n$  minus 1 inverse that is what I have done using these results we will now be generating  $W_n$  from  $W_n$  minus 1 that will give you a slow recursion relation that is what we are aiming for and that I will do in the next class.

$$\begin{aligned}
 \underline{A}_n^{-1} \underline{x}(n) &= \hat{\lambda}^{-1} \underline{A}_{n-1}^{-1} \underline{x}(n) - \frac{\hat{\lambda}^2 \beta_n}{1 + \hat{\lambda}^1 \beta_n} \underline{A}_{n-1}^{-1} \underline{x}(n) \\
 &= \left[ \hat{\lambda}^{-1} - \frac{\hat{\lambda}^2 \beta_n}{1 + \hat{\lambda}^1 \beta_n} \right] \underline{A}_{n-1}^{-1} \underline{x}(n) \\
 &= \frac{\hat{\lambda}^{-1}}{1 + \hat{\lambda}^1 \underline{x}^t(n) \underline{A}_{n-1}^{-1} \underline{x}(n)} \cdot \underline{A}_{n-1}^{-1} \underline{x}(n) = \underline{g}(n) : \text{gain vector} \\
 \underline{A}_n^{-1} &= \hat{\lambda}^{-1} \underline{A}_{n-1}^{-1} - \left( \frac{\hat{\lambda}^2 \cdot \hat{\lambda}^{-1}}{1 + \hat{\lambda}^1 \underline{x}^t(n) \underline{A}_{n-1}^{-1} \underline{x}(n)} \underline{A}_{n-1}^{-1} \underline{x}(n) \underline{x}^t(n) \underline{A}_{n-1}^{-1} \right) \\
 &= \hat{\lambda}^{-1} \underline{A}_{n-1}^{-1} - \hat{\lambda}^{-1} \underline{g}(n) \underline{x}^t(n) \underline{A}_{n-1}^{-1}
 \end{aligned}$$

Please come prepared with this in the next class. Thank you very much.