## **Numerical Methods and Programming P. B. Sunil Kumar Department of Physics Indian Institute of Technology, Madras Lecture - 23 Methods for Solving Non**-**Linear Equations a Comparison**

The last class, we were looking at finding the solutions of non linear functions. We looked at many methods, one which need two guess values either side of the 0 of the function or another method which requires only one guess value. So the first method which need two guess values on either side of the function we called the bracketing methods and the ones which need which require only one guess values where Newton Raphson fixed point iteration and also the secant method. So we will continue looked at Newton Raphson today again.

So in the Newton Raphson method, you remember what we are doing was, we had a function, if you have a function of this form that is f of x versus x, we are looking a function of one variable to start with and then we had x axis on this and then we were looking at where the function would cross 0 that is the solution point which we are interested. So one method of doing this actually plot, take any iteration function point for example if I could take redraw this little bit better.

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So if you had something like this and then if you had initial guess make an one initial guess in this problem, so that that we called  $x_0$  and then what idea was draw a tangent at that point graphically this is was it means we draw a tangent at that point and look at the point where the tangent crosses the x axis. Okay take that as a next iteration point the x value corresponding to that, okay that was our next iteration point and we drew a tangent at that there okay and then we took as next iteration point etcetera. We this value taken

and then we draw a tangent there to get the next iteration point and that is how we continued to get the function that was the summary here, if u have some function which is of this form okay then we make one guess value here I taken as  $x_0$ , you draw a tangent at there and take the point which crosses the x axis and then take that as a x value next iteration point, that is next guess value of the next approximation 0 and then you go there and draw the another tangent and then go to the next point x.



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So that is what we looking at we also look at a program implement this and so here, so at every point we had we find derivative which is f prime of x and the idea was to find the

point and it which crosses the 0. So 0 that, this tangent meet the x axis that gives the formula for the next iterative point. It is a very simple formula where  $x_1$  equal to  $x_0$ minus f by f prime and then this is easy to implement in a program and also we have to saw that converges very fast now compare to any other methods which we are looked at okay that is the advantage of this method is there one, it converges very fast and second is that it needs only one guess value to be begin with but there is also a problem, the problem being that is by f by the formula contains f by f prime of x. So in cases where the f prime of x tend to go very low this can be lead to large errors.

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For example if I have a case like this, okay so you could have function f of x verses x and we could other function going to 0 something like this. Okay so now that is our 0 crossing point. So that, this in this case, the f prime if x itself it extremely small okay in that cases you could get into trouble using this formula, we will discuss and we will show we will look at particular case where thus such situations arise. So write now let us look at the advantage and disadvantage of this function.

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In general we proceed from the  $i$   $i\hbar$  to the  $(i+j)\hbar$ approximation using the relation  $\mathbf{x}_{i+1} = \mathbf{x}_i$ STEP 3: The iterative cycle is stopped when two successive values of  $x_i$  are nearly equal with in a prescribed tolerance

So the advantage being that need only one guess value and then iterate this converges very fast, when it converges okay the case, where it converges it converges pretty fast but that can be cases where it does not converge the reason being that the one of the reason being that the f prime of x go to very small value, an another reason could be another function reason where it need not converges is when you have, when you have functions of a when you have functions of this form and you make this as a guess value, okay this also a problem because the tangent here does not meet the x axis, that can also be a problem and then also we saw cases were they can actually get trap between two trap points.

So there are cases, pathological cases where this thing does not converge. So if it converges and then the convergence criteria being that  $x_i$  minus  $x_i$  plus 1 minus  $x_i$  should divided by  $x_i$  minus 1 should below some predetermined error tolerance which we have put. Okay that is the idea basically idea of Newton Raphson tailor expansion that is we say that the function  $x_i$  plus 1 is determined from function  $x_i$  by tailor expansion and we terminate this at first derivative and we determine that this function  $x_i$  plus 1 should be 0 and we determine h, such that  $x_i$  plus 1 that is  $x_i$  plus h the function value is 0 that is the idea what leads to an very simple formula we saw in the last case, the last lecturer.

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So wherever f prime of x is not equal to 0 then we can write this formula of this form as an iterative formula for the, for the variables.

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If 
$$
f'(x_i) \neq 0
$$
 for all  $x_i$   
\n
$$
h = (x_{i+1} - x_i) = -\frac{f(x_i)}{f'(x_i)}
$$
\n
$$
x_{i+1} = x_i - \left[\frac{f(x_i)}{f'(x_i)}\right]
$$

Another method which we saw was the secant method, in the secant method, again we had two guess values, okay this different from the fixed point iteration or Newton Raphson, so this was the secant method so there still we need two guess values we called  $x_i$   $x_1$   $x_0$  or  $x_i$   $x_i$  minus 1 in general. So the next point there is to determine from this two guess values, so the idea is again that you could have difficulty in computing the f prime of x.

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So in the Newton Raphson formula, we saw that in newton raphson in the Newton Raphson we had formula that  $x_i$  plus 1 is equal to  $x_i$  minus f of  $x_i$  divided by f prime of  $x_i$  at f prime at  $x_i$ . So now the problem is to predetermine the this f prime of  $x_i$  that is the first derivative of the function which we want to solve we are trying to solve the function of this form f of x equal to 0 that is what we are trying to do to find the minima of. So the difficulty might be may arise when we do not know what the derivative of the first function x, that is this function itself could be coming from another program.

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Newton Raphin Xin=Xi

So we do not know actual functional formula of this, we know only the data points. We know that we give x value it gives a number some other program which gives you that and we need to find still 0s function we do not know the derivatives. So in that case, we determine the derivative from something like backward difference scheme, so that is what secant method basically uses. So we begin with two points, so we need two guess values to begin with and then we compute the derivatives from derivative, from that this 2 guess values using this formula that is f of x, f prime of  $x_i$  that is equal to f of  $x_i$  minus f of  $x_i$  minus 1 divided by  $x_i$  minus  $x_i$  minus 1.

So this is the normal backward difference scheme, so we can use that so one would wonder are we are doing same two point iterations which we done at beginning that is the bracketing method. Now this, this is not because  $x_i$   $x_i$  minus1 need not be on either side of the 0 okay that is one important point to remember here. We do not take  $x_i x_i$  minus 1 as either side of the 0 that is we do not need f of  $x_i$  minus 1 to be positive, when f of  $x_i$ minus 1 to be negative we do not need that this can be both on either side, the same side still get solution to that. So this is basically a slight modification of the Newton Raphson, where in Newton Raphson we had the knowledge of the f prime of x, we did not have in cases where we do not have knowledge we could use this formula and using two formulas in two points and then iterative.

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So in the basic Newton raphson we will the f prime of x by particular formula, so you remember Newton Raphson was  $x_i$  plus 1 equal to minus f of  $x_i$  divided by f of  $x_i$  minus f of  $x_i$  minus 1  $x_i$  divided by f prime of  $x_i$  that is what Newton Raphson  $x_i$  minus 1 equal to  $x_i$  minus f of  $x_i$  divided by f prime of x. So now f prime of x that is the first derivative of f is now replaced by this backward difference scheme and we can write this in a form that varies by now given by this just rearranging the terms.

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Okay graphically this could mean this that you have the function the red line, if the function of this form to be minimized whose 0 have to be find okay that is what we want to find out this is crossing point here is. So we guess with starting point with  $x_i$  minus  $x_i$ two guesses values in this particular example which was written either side of 0. We do not need to know that, we choose it from choose it on same side itself and then now instead of drawing a tangent that we can draw a secant just a line connecting two points so the backward difference for the tangent could be quiet off right, when the two points are very far apart write that is what it is. So in this two different point the two points

which we guess  $x_i$  is i minus 1 and that is very far away and then and then which connect the secants and this line crosses the x axis here, so we take as a next iteration point.

So now here comes the difference between this secant method and the bracketing method, in the bracketing method what we did was we replace  $x_i$  minus 1 always by f of  $x_i$  minus 1 is negative. We will look at whether f of x are minus 1 or f of  $x_i$  which was negative and we will replace that particular point by this that is if f of  $x_i$  plus 1 here will replace x of i if x of i is negative because f of  $x_i$  plus 1 is negative otherwise you would replace this point that is the bracketing method but in this case we will always replace  $x_i$  minus 1 by  $x_i$  and  $x_i$  by  $x_i$  minus 1 that is the tangent the secant is now drawn between  $x_i$  and  $x_i$  plus 1 that is this line the next line which is below

Okay that is the line which will be next draw and look at were it crossing points that is here and then we will draw between these two points now we will draw this point and we will draw this two points that is the method okay so we will continue to do notice that when we went to the second case that is started from  $x_i$  minus 1  $x_i$  and then we went to  $x_i$  $x_i$  plus 1 then you have the secant is the same side of the 0



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So this will not happen in the bracketing method write the bracketing method we would write say the new point  $x_i$  plus 1so now f of  $x_i$  plus 1 is negative and f of  $x_i$  is also negative I will keep the  $x_i$  minus 1, I will throw away this point now I will iterate between 3 2 point okay in the bracketing method I will draw a line connecting this point to this point  $x_i$  minus 1 but here is not done we just throw away and then we will draw a line between these two points. So I have the clear difference between the secant method and the bracketing method.

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So that is the points is line is draw connecting f of  $x_i$  minus 1 and f of  $x_i$ , okay were the points crosses the x axis is taken as  $x_i$  plus 1 and then we will draw something between  $x_i$ and  $x_i$  plus 1. So that this  $x_i$  plus 1 is always dropped okay to get the next point now this is different from the bracketing method in that sense.

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Okay, so now we will saw some example of this, now we just look at some example, we are using secant method this equation 1 minus x square plus log 1 plus x that is what we look at now. So we have a program here called that is a this program basically implements, that remember in our last class, we discuss general framework for this

program that is the main function we have here okay that is start from here and ends here small main function which take two guess values.

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So this program basically already does is, it defines what is the method which we are going to use here, it says okay now this is secant method that is what we are going to use this is similar to this, okay now I want to show you is this comparison with this and the false position. Okay so here, let us the bracketing method this is we are going to use here the  $x_2$  so this is the formula which we are going to use  $x_2$  is determined by that formula which we just saw this is a formula which we are going to use write for the from  $x_1$  to x <sup>2</sup> we use this formula that is what shown here.

So that is what shown in here the function value at  $x_1$  multiplied by  $x_0$  minus this function value at  $x_0$  multiplied by  $x_1$  divided by function value  $x_1$  minus the function value  $x_0$  determined  $x_2$ . So then x 0 always replace by  $x_0$  by  $x_2$ , okay so we do not look at for what function at  $x_2$  value to determine when  $x_0$  should go to  $x_1$  or  $x_1$  or  $x_2$  should go to  $x_0$  should replace by  $x_2$  or  $x_1$  should replace by  $x_2$  we just replace both by the next iteration point that this is  $x_2$  is always given by this function and we always replace  $x_1$  by  $x_2$  and  $x_0$  by  $x_1$  that is the method, that way is different from the false position method and so then this secant method we just called here we will two guess values here that is the function the main function would simply read that to guess values okay and it called this method, it changes to secant method.

So from false position, we go to secant method that is what we have to use the secant method this function now we pass  $x_0$  and  $x_1$  whatever we read as the initial guesses into this value  $x_0$  and  $x_1$  to the, to the program secant method and then we also passed point to the function which we want to whose 0 we want to find out that is the general framework for the main program it is all does it is initial guesses determine which method to use the secant method.

Okay and then it will passed this to guess values and the pointer to the function which we want to minimize the pointer the function called func, so we look at what is func is func is 1 minus x square plus log 1 plus x. Okay the func simply return the function value at that point that is all the program the needs, it does not need the derivative unlike in the case of Newton Raphson where we need to find the derivative.

Okay then we just, we start with the error set to be one and then it does the iteration and till the error is less than some predetermine tolerance. Okay and the error being  $x_1$  minus  $x<sub>2</sub>$ , the previous guess to the solution the minus the present guess divided by present guess absolute value the error, okay that is the program and then we just start with two guess values and see what we get okay.

We need, we compile the program, we need two guess values just give it as 2 and 1, okay that is the 0. So okay, that it converge very fast okay compare to if you remember the bracketing method again this is as fast as the case of in the case of the Newton Raphson this is converges very fast, that is the we have printing out the error this is the error okay that is the function value and this is the x value which we got. We can see that we started with error being ".21" gone into a very small value function is converge to 0 to 0.

We could so the function itself which we looked at we looking at 1 minus x square plus log 1 plus x function, we just we looked at okay and so we plot the line also we will look at the this this the function which we saw just plotted that is the function. So we can see the error 0 is somewhere around "1.3" that is what we just did but we started with the guess which is 1and 2 that is what we guess as initial the initial guesses the 1 and 2, we could try something different we could try for example "1.5" 1.25" what we get that is that is the same side of the 0 that is makes different from the false position method. We could just do that and "1.5" and "2.5" we can see that it converges the same the rate which converges pretty fast again to "1.36".

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Okay that shows that, we do not need to actually do the, we do not need to actually make the guess at the same side, the 2 different sides 0 in this particular method that is make different from the false position method and easier, to easier to implement in that sets okay so going back to our discussion here. So this is the method this is the last method which we look at, okay so we had 454 different method we are the midpoint method just

begin with we had midpoint method we need it is bracketing that is we always took the next guess as  $x_i$  plus  $x_i$  plus  $x_i$  plus 1  $x_i$  plus  $x_i$  minus 1by 2 that is our next ever  $x_i$ ,  $x_i$ minus 1 we made sure on either side of 0 of the function and then we look at the false position method which again took  $x_i$   $x_i$  minus 1 and then we drew a line between connecting this 2 points, the  $x_i$ , f of  $x_i$  and  $x_i$  minus 1 f of  $x_i$  minus 1 and look at that point cross the 0 were it crosses the x axis and we took at the next guess and we replaced one of the points by the new guesses such that we the true solutions bracketed between this 2 values then we look at the fixed point iteration method were we had f of  $x_i$  as f of x we written it as g of x minus x and then f of x equal to 0 will become g of x minus x equal to 0 or x equal to g of x.

So we just at iterations that  $x_i$  plus 1g of  $x_1$  f of  $x_i$  that needed only one guess and then we look at the Newton Raphson method and were we had the  $x_i$  plus 1 given by  $x_i$  minus f by f prime of  $x_i$  that based on tailor expansion around  $x_i$  and then we look at the secant method were the f prime of x Newton Raphson which is replaced kind of different scheme and that is saying that f prime of  $x_i$  is f of  $x_i$  minus f prime f of  $x_i$  minus f prime of  $x_i$   $x_1$  divided by  $x_i$  minus  $x_i$  minus 1 that is, that gives the secant method where we again we need two guesses to begin with but it does not have to be on the either side of the function or two guesses do not bracket the true solutions that is the method we looked at.

Now we will look at various convergence of this one point iteration scheme that is where we need to make only one guess what is the convergence rate of that what is the rate in fixed point iteration scheme and Newton Raphson scheme that is what we looked at the advantage of using Newton Raphson will become pretty clear if you look at this plots where newton Raphson works that is the best method that is everybody using everybody uses so whenever Newton Raphson works that is the best method so the reason for that is clear from this.

Let us look at fixed point iteration scheme first. So in that case we write  $x_i$  plus 1 as g of  $x_i$  that is what fixed point iteration which we just now we had and then we let say x of r is our true solution, okay then we would say that  $x_i$  plus 1 is g of x but if then true solution g of  $x_r$  equal to  $x_r$  if it is true solution, now if its not a true solution and then we have this error right the  $x_i$  plus 1 minus  $x_r$  that is our error okay so we call that is a error in the i plus 1th iteration. So I go this is clear, so we say that  $x_i$  plus 1 is equal to g of  $x_i$  that is our iteration scheme and then we have if this is the true solution then g of  $x_i$  this x of i x of i plus 1 should be equal to  $x_i$  we called that is  $x_r$  that is been true solution. So the difference between  $x_i$  plus 1 and true solution is our error right.

So that is our error in the i plus 1 iteration scheme okay, so now g of  $x_i$  plus 1 is g of  $x_i$ sorry  $x_i$  plus 1 is g of  $x_i$  and  $x_i$  is g of  $x_i$  because that is true solution right hand side and so we could use that formula here for the error okay. So  $e_i$  plus 1 which is  $x_i$  plus 1 minus  $x_r$  that is is the difference between the value obtained at I th I plus 1th iteration to the value to the true value is equal to the value of function g of function not the f g at  $x_i$ minus g of  $x_i$ .

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So we can write that okay then you remember the mean value theorem which we used in the case of polynomial interpolation that is to say that we can always find a point it be called at Etta I between  $x_i$  and  $x_r$  such that g of  $x_r$  minus g of  $x_i$  divide by  $x_r$  minus  $x_i$  is the derivative of g at that point. Okay we can always use that so we will use that term property that g um one point where between  $x_r$  and  $x_i$  where we have the derivative is equal to the equal to this mean value, there is  $x_i$  minus  $x_r$  g of  $x_i$  minus g of  $x_r$  divided by  $x_r$  minus  $x_i$  and then we can write the g prime of Etta I in to  $e_i$ , now remember this  $x_i$ minus  $x_r$  would be the error at the i th step right, So if  $x_i$  plus 1 minus  $x_r$  is the error I plus step  $x_i$  minus  $x_r$  is the error the i th step.

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So I can multiply by this by  $e_i$  and write it as g prime of Etta I in to  $e_i$  as g of  $x_i$  minus g of x i right. So the minus sign here the minus sign here, so it is  $e_i$  there should be  $e_i$  plus 1. So the formula we want to do is following that is so what we saying is that I have g of  $x_i$  and so g of  $x_i$  minus g of  $x_r$ , so I want to write g of  $x_i$  minus g of  $x_r$  divided by  $x_i$ minus  $x_r$  we want to call at g prime at Etta I using the mean value theorem. So Etta I is some point between  $x_i$  and  $x_r$ , so Etta I is greater than  $x_i$  less than  $x_i$  somewhere in between x i and x is this value Etta. So then  $x_i$  minus  $x_i$  is my e i, so I can write g prime of Etta I in to e i as g of  $x_i$  minus g of this  $x_r$   $x_r$  but g of  $x_r$  is nothing but  $x_i$  plus 1, okay

this is g of  $x_r$  is  $x_r$  that is  $e_i$  plus so we have a simple formula its says g prime of Etta I g prime at Etta I in to  $e_i$  equal to  $e_i$  plus 1 that is the formula which we need to use.

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$$
g'(\eta_i) = \frac{g(x_i) - g(x_i)}{x_i - x_i}
$$
\n
$$
g'(\eta_i)E_i = g(x_i) - g(x_i) = E_i
$$
\nThat is we have linear convergence.

So that formula tells that we have a linear convergence okay its means the error in the i plus 1 is linearly related to the error in the i th step okay that is the point which I want to emphasize here. so the error in the i th step is related to the error in the i th step by some derivative of function some point, it is not important what this is some derivative but it is a linear derivative at some point, it is a but linearly related these two are linearly related

so this 2 errors are linearly related. So we have a linear convergence that is what we would say we have a linear convergence.

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So it should be  $e_i$  plus 1 and then the next scheme that is we look at the same thing for Newton Raphson so for now in this particular case we had g of  $x_i$  has  $x_i$  plus 1. So that is were scheme, we had  $x_i$  plus 1 given by g of  $x_i$ . So when we look at the Newton Raphson we have this formula  $x_i$  plus 1 is equal to  $x_i$  minus f of  $x_i$  by f prime of  $x_i$ . So let us see whether we could again using the same definition for error as  $x_i$  plus 1 minus  $x_i$  as e of i plus 1 what kind of relation between  $e_i$  and  $e_i$  plus 1, we can get this in this particular

following. That is what we look it now okay that is so we have  $x_i$  plus 1 given by  $x_i$  f of  $x_i$  by f prime of  $x_i$ . Okay and then so now if f of  $x_r$  is the true solution in this case f of  $x_r$ would be 0 right so then I have f of  $x_i$  if I expand around f of x. (Refer Slide Time: 31:48)

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Okay so if expand around f of  $x_i$ , so I get f of  $x_i$  as f prime of  $x_i$  and  $x_r$  minus  $x_i$  plus f double prime of  $x_i$  etcetera right. So that is the tailor expansion around  $x_i$ , so I tell you to expand the expansion around guess x,  $x_i$  okay and I say go to  $x_r$  from that okay if  $x_r$  is the true solution then the function value is 0, so I have 0 equal to f of  $x_i$  plus f prime in to  $x_r$  minus  $x_i$ , f double prime the second derivative  $x_r$  minus  $x_i$  whole square by 2.

So I can rewrite that as you know f prime of  $x_i$  in to  $x_i$  minus  $x_i$  plus 1 minus  $x_i$  as this. I am just rewriting the function. Okay, so I have just rewriting this, this whole function that I have written as f prime of  $x_i$  in to  $x_i$  plus 1 minus  $x_i$  is now given by f prime of  $x_i$   $x_r$ minus  $x_i$  and if double prime of  $x_i$  in to  $x_r$  minus  $x_i$  by 2 whole square. So then I can rearrange this again, so basically just I take function to left hand side and then write as f prime of  $x_i$  in to  $x_i$  plus 1 minus  $x_r$  equal to f double prime  $x_i$  in to  $x_r$  minus  $x_i$  whole square by 2. So that is the case, so we have then obtained action between  $x_i$  plus 1  $x_r$  is  $e_i$ plus 1. We are doing exactly as what we did in the case of fixed point iteration and then now we have  $x_r$  minus i as  $e_i$  this  $x_r$  minus  $x_i$  whole square, so  $e_i$  square.

So we have now found that  $e_i$  plus 1 is equal to okay we have  $e_i$  plus 1 is given by this is equal to f double prime divided by f prime f double prime divided by f prime in to  $e_i$ square, okay so in this case the Newton Raphson case we have  $e_i$  plus 1 it is the error at I plus one step being related to the error in the I th step if this quadratic relation its  $e_i$  plus 1 is equal to e<sub>i</sub> some quantities some derivative some quantity which involves the second derivative and the first derivative multiplied by  $e_i$  square.



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So again where if the f prime of x is not too small this is quadratic convergence we have that is the reason why Newton Raphson convergence much fast much faster than any other method provided here f prime of  $x_i$ . Okay that is the that is the summary here we just used this particular idea that is we can write you know f of  $x_i$  plus f of tailor expansion this function around  $x_i$  and we say that we go to  $x_r$  that that means we can write it as f prime of  $x_i$  in to  $x_r$  minus  $x_i$  and double prime of  $x_i$  in to x minus  $x_i$  whole squared etcetera and then I can use this f of this value as you know  $x_i$  minus 1  $x_i$  plus 1 minus  $x_i$  in to f prime of  $x_i$ . So that also gives me f of  $x_i$  right, so two ways of getting it, so this f of  $x_i$  also given by  $x_i$  plus 1 minus  $x_i$  in to f prime of  $x_i$  that is what I am comparing here.

(Refer Slide Time: 34:45)



(Refer Slide Time: 35:42)



I compare these two and then from there I get the error by subtracting this term from this term when I writing this form so I get  $e_i$  plus 1 and I get  $e_i$  square on the right hand side that is the simple formula for the linear as quadratic convergence of the Newton Raphson method. So we saw, what we see here, we see that in the case of fixed point iteration, we have linear convergence, where in the case of Newton Raphson we have quadratic convergence. So that is what the point is.

(Refer Slide Time: 36:03)



Okay so now this again points of fact that Newton Raphson is the best method provided we do not have f prime of  $x_i$  going to, going to very small value. So one place where that actually comes when we have what is known as multiple root that is suppose we have a function which is of this form, that is suppose we have a function which is of this form which is  $x_i$  minus 1 whole square in to  $x_i$  plus 2  $x_i$  minus 2. So now we know that where the root functions are, this function roots would be at x equal to 1, if definitely root of this function. Okay so now if I look at the derivative of this function, f prime of  $x_i$  okay that is lets expand this easier to see this way so we can write function  $f$  of x as x square minus 2 x plus 1 in to x minus 2. So that is x cube minus 2 x square plus x, so we have a function of this form that is the function we have and because we know form this we can easily see this okay, so x equal to 1 this is f at 1 is 1 minus 4 plus 5 minus 2 that is 0 right that is, the that is which is 0 okay. So look at f prime of x at 1, okay at x equal to 1 that is what we want to look at.

So we look at f prime of x equal to 1 f prime of x is  $3 \times$  square minus  $8 \times$  plus  $5 \text{ okay}$  so then we look at x equal to 1 that value of that is 3 minus 8 plus 5 we get that as 0. So that is this so problem point for um Newton Raphson. So we had we know that root is equal to one okay so then we saw that f of x at 1 is actually 0 that is the root but then how do we go to Newton when Newton Raphson how do we approach this point. So we approach this point by using the formula that  $x_i$  plus 1 is  $x_i$  minus f of  $x_i$  minus f of  $x_i$  divided by f prime of  $x_i$  that f prime at  $x_i$  but f prime at  $x_i$  is 0 so as you go towards this point so of course we are not interested exactly at point f prime at this, at that point x equal to 1 that is the root both f of x and f of x, f prime of  $x_i$  are 0. So the question then is what goes to 0 faster okay so that if this goes to 0 faster then we are in travel that is an example. So I am just trying to giving you reason a point where it can have travel.

(Refer Slide Time: 40:03)



So if you actually plot this function so you would see that this point the derivatives is also 0 and then what happens to either side of the function right if you look at a value which is slightly larger. So since the first derivative also go to 0 this function actually does not change sign then okay so see it touches that 0 and goes away. So this kind of points depending upon f prime of  $x_i$  goes faster f of  $x_i$  goes faster you can get difficulties.

(Refer Slide Time: 40:37)



So if f prime of x goes to 0 lower than f, fx then of course we can it will converts so a better formula to use this point to use the second derivative also and that is what we would see in implementation here, I will show you that implementation this okay here is

the this is the formula which your using before this  $x_2$  is equal to  $x_1$  minus the function value divided by the derivative of the function value function that was we are using before, this is the derivative of the function. So this this formula is one replaced by slightly by different formula which is  $x_2$  is equal to  $x_1$  minus the function value multiplied by the derivative of value divided by the derivative multiplied by derivative square f minus, f minus derivative 2 that is we are going to write the formula that is  $x_i$ plus 1 equal to  $x_i$  minus function now is multiplied by function at  $x_i$  is multiplied by f prime of  $x_i$  divided by then f prime of  $x_i$  square minus, okay that is basically just taking the 2 derivatives of this function itself taking the derivative here and then replace by the formula that okay that is what we are doing here.

So we are saying that  $x_i$  plus 1 now  $x_i$  before we had f of  $x_i$  by f prime of  $x_i$  so in the case now what is called multiple roots that is you have  $x_i$  minus 1 whole square into  $x_i$  minus  $2$  or  $x_i$  minus whole cube thinks like that where many derivative it that vanishes okay that is in this case the two derivatives the first the function and its derivative vanish at the root but, if you could if the cases where you know if  $x_i$  plus 1 whole cube for example, then you would have the first derivative and second derivative would vanish at this point okay.

(Refer Slide Time: 43:07)



So those cases it will be advantage to use the formula of this form that is  $x_i$  plus 1minus equal to  $x_i$  plus f of  $x_i$  and f prime of  $x_i$  divided by f prime of  $x_i$  square that is first derivative squared minus the function to the point multiplied by second derivative. So the disadvantage is of course to that now we also need also to determine the second derivative, so where the second derivative is available and then this is the faster method for convergences, just sees that right now. So let us use the whole formula, so this program here actually minimize the function of this form that is function here, hope you can see the function, that is the function is x to the power four minus  $x_6$  x cube plus 12 x square minus 10 x, I will write this function.

(Refer Slide Time: 43:09)



(Refer Slide Time: 43:51)



So we will try to minimize the function of this form that is the x to the power 4 minus  $6x$ cube plus 12 x square minus 10 x plus 3, okay so you want to find the 0 of this function so I plot the function here. So I am just plotting this function here, that is x to the power minus 6 x cube plus 12 square minus 10 x, 10 x plus 3. So I am just plotting that, so that is given here, so you notice that it goes to 0 point around 1 right, set one goes to 0 but it goes to 0 extremely slowly that is it almost flat this, the first derivative and second derivative vanishes.



So now we will use Newton Raphson to find the 0. So let us start from point 5 something and see how fast it converges to that point using our old formula for Newton Raphson method okay. So we will use that, so we will compile this program. So remember that we are using here is, this same function that is x to the power four this p or w is the power function built in function gives x to the power 4 here and x to the power 3 in to 6 x to the power 2 in to 12 and 10 x plus 3 that is what the function we have, okay and then we are using the simple scheme that is, we are going to use the normal newton Raphson that is  $x_2$  is now  $x_1$  minus f by derivative function derivative here.

So here I called this function okay which is pass on to method, I am using is Newton Raphson again, so initial guess value in the main program, okay I have one initial guess value which I defined, okay and it passes the program called Newton where initial guess value is passed and the pointer to this function is passed and this return the 0 and the program will just print the 0 out. So now the function Newton takes this pointer as some other value called function does not matter.

So then  $x_1$  is the initial guess value and, the function now needs this this thing called function that is basically func right. So func now takes an argument if 1 x value okay and 1 point where which is actually the function value itself okay and array in this array now written array of derivative that array 0, the first element of array does not derive 0 take the first derivative and derive 1 takes the second derivative.

So that is 0 and one first derivative and second derivative of the function that is what it written but to begin not to use that lets just use only the first derivative use by f by divided by the first derivative formula okay start of f where f is a pointer here, as we saw this is a pointer this is an array of derivative. So the first element being the first derivative and a second element being second derivative otherwise the program is same as before. Okay so now this  $x_2$  is x minus f divided by derivative of f, so that is what we are going to use in this program. So we will run this program okay, so we will run this program now with this particular function, so give some initial value ".8" and we see that the uses convergences. So it converges to 1 we saw that the root was around 1 in that we plot at this thing converges to 1 okay, so but this takes to many steps to converge, okay it has to go through many iteration scheme to converge, okay so but we will look at the slightly different formula.

So that is we will now look at this case where we have so what we have here is now  $x_1$  minus f in to derivative the first derivative divided by the derivatives squared the first derivative squared minus f function in to the second derivative. So that is the formula which we are going to use now, so we will run that formula. So we will compile the program with that formula and then we will run the same iteration itself. So again this converges to 1 but we will see that converges much faster see, we started from here and it converges much faster here, then the previous iteration.

Okay that is the thing which I want to tell you that in this case where we use this modified formula that is where we use the derivative of 0 multiplying the function and also use the second derivative okay the convergences rate is much faster, okay then the formula which uses only the first derivative, okay you can see that in various functions which you can try out yourself. So the Newton Raphson with the second derivative converges much faster than Newton Raphson first derivative provided of course that which you would be find the second derivative of the function. So this works much better and the round of errors and other errors are much lower in this case where we use the second derivative.

(Refer Slide Time: 44:40)



(Refer Slide Time: 49:39)

Simultaneous Nonlinear Equations We can trivially extend Newton-Raphson scheme to find the solution to a set of equations of the form  $f_i(x_i, x_i, \ldots, x_n) = 0$   $i = 1, 2, \ldots n$ Taylor expansion around a set of guess values,  $(x_1, x_2, ..., x_n)$  leads to a set of equations,  $f_i(x_1 + h_1, ..., x_n + h_n) = f(x_1, ..., x_n) + h_j \frac{\partial f_i}{\partial x_j}$ Which can be solved using matrix elimination

So before we end this session on the Newton Raphson method and finding the zeros of non-linear function, okay we will just look at one more problem that is what happens if you have instead of one function, we have many function and we want to find a simultaneous root of this set of non-linear functions. Okay given for symbolically here you could have a series of function n function okay which has n unknowns, so we could you know for example, we could just have a function say x square minus xy equal to 0 and then you have some other function which is y square x plus  $2y$  plus  $3x$  equal to  $0$ some function like this, okay you have 2 unknowns x and y and then you have 2 equations.

(Refer Slide Time: 50:41)

 $3 + 12x^2 - 10 \times 13$ 

Okay so you could have series of function of this form, you could in principle have a series of function, we call them  $f_1$ ,  $f_2$ ,  $f_3$ ,  $f_n$ ,  $f_n$  are unknowns. So in that case how do we find the solution of this equations again it turns out the Newton Raphson pretty easy because we can make the guess value for all the solutions that this case n values to be found find the solution this function the set of function and then, so let us assume that the  $x_1, x_2, x_3$  up to  $x_n$  and then we want to go and find out the values of  $x_1, x_2, x_3$  etcetera, such that all those functions goes to 0 right all of them goes to 0 simultaneously. So the way to do that is again expand around that guess value which we have wee do tailor expansion, so when we do a tailor expansion such form, so we would now have f of let us take an example  $x_1$ ,  $x_2$ ,  $x_3$  equal to 0 that is what we want to find out solution of this. Okay we start with some  $x_1^0$  start with some  $x_1^0$ ,  $x_2^0$  and  $x_3^0$  as our guess solution and then we will write f of  $x_1, x_2, x_3$  as the value at  $x_1^0, x_2^0, x_3^0$  plus derivative of function by  $x_1$  right.

(Refer Slide Time: 50:44)



So that is the first derivative at  $x_1^0$ ,  $x_2^0$ ,  $x_3^0$  in to  $x_1$  minus  $x_1^0$  and then we have the derivative of the function plus the derivative of the function at with respect to  $x_2$  second variable again at  $x_1^0$ ,  $x_2^0$ ,  $x_3^0$  in to  $x_2^0$  minus  $x_2$  minus  $x_2^0$  right and then we have the next one that is derivative of function with respect to  $x_3$  at the guess the initial guess value in to  $x_3$  minus  $x_3^0$ . So that is what we call  $h_1$ ,  $h_2$ ,  $h_3$  okay, so I can write the in the symbolic form as f at  $x_1^0$  del f by del  $x_j$  in to  $h_j$ , so were  $h_j$  is  $x_2$   $x_j$  minus  $h_j$  0 that is what I can write sum over all the  $j_s$ , so sum over all the unknowns okay that is what I have written here.

(Refer Slide Time: 53:33)

So that is this function I have written as. So then I can say that, okay as same as before same as one variable okay left hand side should be 0, so then I have a set of linear equations because I know the derivative for and then I have  $x_j$  del f by  $f_i$  by del  $x_j$  is equal to okay that is what I would have here.

(Refer Slide Time: 53:35)

Simultaneous Nonlinear Equations We can trivially extend Newton-Raphson scheme to<br>find the solution to a set of equations of the form  $f_i(x_1, x_2, ..., x_n) = 0$   $i = 1, 2, ...$ Taylor expansion around a set of guess values,  $(x_1, x_2, ..., x_n)$  leads to a set of equations, <u>F)</u>  $= 0$  $f_i(x_1+h_1,...,x_n+h_1) = f(x_1,...,x_n) + h_i$ Which can be solved using matrix elimination

(Refer Slide Time: 54:36)



Again I have to write both the cases, so either 3 equations like this  $f_1$  function  $f_1$  and that is for function f<sub>1</sub>. Okay I will have similar equation for  $f_2$  and  $f_3$  either 3 equations right. So will actually have three equations for this we will have  $f_1 f_2$  here which is the 3 unknowns I need 3 equations and then I will have a  $f_3$  of  $x_1, x_2, x_3$  equal to 0, there are 3 equations so to expand all the three functions in this form okay that is the summary which you will get so you will get 3 linear equations and we know how to solve a set of linear equations, we are going to look at elimination method etcetera. So we can use those set of equations to solve particular problem I have just briefly show you that thing here.

(Refer Slide Time: 54:38)

Simultaneous Nonlinear Equations We can trivially extend Newton-Raphson scheme to find the solution to a set of equations of the form  $f_i(x_i, x_i, ..., x_n) = 0$   $i = 1, 2, ...$ Taylor expansion around a set of guess values,  $(x_1, x_2, ..., x_n)$  leads to a set of equations,  $f_i(x_1+h_1,...,x_n+h_1)=f(x_1,...,x_n)+h$ Which can be solved using matrix elimination

So we have, if you have system of equations okay, so if you have system of equations to look at, okay again we will have to use some metrics method okay set have non-linear equations here and this function. So this function has before now the main program is same as before only thing is now, our function will have set of equations to be given okay, so now that function now we have to construct this metrics equation, okay that is I am going to show here.

So here, so this called its function okay we have x is now the initial guess value all same as before, so we had the function which returns the function value now the function value return in an array okay and derivatives are written in a 2 d array and the guess value itself is now an array. Okay so that is would we see the details of this program and the implementation of it in the next lecturer, but just for the time being look at this yourself. So what we have to do is now the modification from the earlier program would be just that the when you call the function value now we have to give it in array of initial guesses because there are many unknowns and then the function return as itself as an array1 d array because, one dimensional array because it has many function and the derivative now as a 2 dimensional array of derivatives we will look at this program in the in the next class.

(Refer Slide Time: 55:00)

