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**NP-TEL
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Course Title

**Finite element method for structural dynamic
And stability analyses**

**Lecture – 13
Mathematical preliminaries and terminologies;
Euler's forward and backward difference methods.**

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Finite element method for structural dynamic and stability analyses

Module-5

Time integration of equation of motion

Lecture-13: Mathematical preliminaries and terminologies;
Euler's forward and backward difference methods



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We'll begin discussion on a new topic today, this is on time integration of equation of motion,

Numerical integration of equations of equilibrium

Consider a N -dof system

$$M\ddot{U} + C\dot{U} + KU + R[U(t), \dot{U}(t), t] = F(t)$$

$$U(0) = U_0; \dot{U}(0) = \dot{U}_0$$

Remarks:

- This equation constitutes a set of semi-discretized system of coupled second order ode-s. That is, these equations have been obtained after discretizing the spatial variables.



This set of equations constitutes a set of initial value problems.

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so at the end of our previous discussions we have seen that the governing equation of motion typically is formulated in this form $M\ddot{U} + C\dot{U} + KU$, for sake of generality I am now introducing a nonlinear term we have not discussed how this originates, but we can believe that this type of terms would arise if we include nonlinear behavior either in strain displacement relations or in stress strain relations, so this is the equation of motion, and these are the specified initial condition, so this equation constitutes a set of coupled second-order nonlinear ordinary differential equations, we say that these equations are semi discretized equations because in arriving at this equation we have discretized space but the time is still a continuous parameter, so they also constitute a set of initial value problem, so these are a set of ordinary differential equations, semi discretized ordinary differential equations which constitute an initial value problem and these equations are coupled.

- The time variable, t , however, is still continuous.

We consider now the problem of discretizing in time.

We consider solution of the above equation at a set of discrete time instants $t_0 < t_1 < t_2 < \dots < t_n < \dots$ with

$$\Delta t_n = t_{n+1} - t_n.$$

- The basic idea is to replace the derivatives appearing in the above equations by finite difference approximations and then solve the resulting algebraic equations.



Now we consider the problem of discretizing in time so what we aim to do is to we consider solution of this equation at a set of discrete time instants ordered as $T_0, T_1, T_2, \dots, T_N$ with ΔT_N being the step size, $T_{N+1} - T_N$. The basic idea here is to replace the derivatives appearing in the equation of motion by finite difference approximations and then solve the resulting algebraic equation that is a main idea. Now to be able to do that what we will do is we

Equations in standard form for a N -dof system

$$M\ddot{U} + C\dot{U} + KU + R[U(t), \dot{U}(t), t] = F(t); U(t_0) = U_0, \dot{U}(t_0) = \dot{U}_0$$

$$\Rightarrow \ddot{U} + M^{-1}C\dot{U} + M^{-1}KU + M^{-1}R[U(t), \dot{U}(t), t] = M^{-1}F(t)$$

Define $X_I(t) = U(t)$ & $X_{II}(t) = \dot{U}(t)$ and

$$x(t) = \begin{Bmatrix} X_I(t) \\ X_{II}(t) \end{Bmatrix} = \text{system state vector}$$

\Rightarrow

$$\dot{X}_I = X_{II}$$

$$\dot{X}_{II} = M^{-1}F(t) - M^{-1}CX_{II} - M^{-1}KX_I - M^{-1}R[X_I, X_{II}, t]$$

$$\begin{Bmatrix} \dot{X}_I(t) \\ \dot{X}_{II}(t) \end{Bmatrix} = \begin{bmatrix} 0 & I \\ -M^{-1}K & -M^{-1}C \end{bmatrix} \begin{Bmatrix} X_I(t) \\ X_{II}(t) \end{Bmatrix} + \begin{Bmatrix} 0 \\ -M^{-1}R[X_I, X_{II}, t] \end{Bmatrix} + \begin{Bmatrix} 0 \\ M^{-1}F(t) \end{Bmatrix}$$

\Rightarrow Equation in state space form given by

$$\dot{x}(t) = Ax(t) + F(t); x(t_0) = x_0; x(t) \text{ is } 2N \times 1.$$

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will reorganize the equation of motion in a slightly different form, so this is the equation of motion that we have $M\ddot{U} + C\dot{U} + KU + \text{nonlinear terms} = F(t)$ and specified initial conditions. Now I pre multiply by M inverse so this equation now becomes, takes this form. I will introduce now a new set of variables X_1 and X_2 , X_1 is $U(t)$, X_2 is $\dot{U}(t)$, I can define another $2N \times 1$ vector in which I assemble X_1 and X_2 as shown here, we call this as system state vector, so this is a state vector consisting of displacements and velocities at the end degrees of freedom.

Now what is \dot{X}_1 ? \dot{X}_1 is \dot{U} , \dot{U} is X_2 , so this is $\dot{X}_1 = X_2$, \dot{X}_2 is \ddot{U} so that I obtained from the governing equation and we write in this form. Now I will assemble this equation in the matrix form, I will have \dot{X}_1, \dot{X}_2 is equal to this matrix into X_1, X_2 plus the non-linear term, plus the excitation term. Now I can rewrite this set of equations in a general form as $\dot{X} = A X + F(t)$ where A , this vector A is $2N \times 1$, we say that this equation is in state space form, by state I mean a displacement and velocity vector together they had constitute the state, and this equation is said to be written in the configuration space where we have only displacements and we get second order differential equations, in state space we have a set of $2N$ first order coupled ordinary differential equations which are initial value problems and we say that the equation is in the state space form.

The set of N coupled 2nd order ODE-s

$$M\ddot{U} + C\dot{U} + KU + R[U(t), \dot{U}(t), t] = F(t); U(t_0) = U_0, \dot{U}(t_0) = \dot{U}_0$$

have been thus recast as the following set of $2N$ first order coupled ODE-s

$$\dot{x} = a[x(t), t]; x(t_0) = x_0; x(t) \text{ is } 2N \times 1.$$

Denote by $x(t, x_0, t_0) = \text{solution of } \dot{x} = a[x(t), t] \text{ with } x(t_0) = x_0$

Discrete time approximation

$$\text{time: } t_0 < t_1 < t_2 < \dots < t_n < \dots; \Delta t_n = t_{n-1} - t_n$$

Denote $y_n = x(t_n, x_0, t_0)$

How to approximate \dot{x} in terms of y_n ?



So what we have done is the set of N coupled second order ordinary differential equations given by this in the configuration space have been thus recast as the following set of $2N$ first order coupled ordinary differential equation. Now what I do is I introduce a notation $X(t, x_{\text{naught}}, t_{\text{naught}})$ I denote solution of this differential equation with $X(t_{\text{naught}}) = X_{\text{naught}}$, so there is T_{naught} , X_{naught} , and T of course is the independent variable. In discrete time approximation, time will be discretized as increasing sequence $T_{\text{naught}}, T_1, T_2, T_N$ with steps as ΔT_N , as I mentioned before and I denote the value of the system state at $T = T_N$ by Y_N , so Y_N is $X(T_N)$ where initial conditions at $T = T_{\text{naught}}$ is X_{naught} . Now the main question is how to approximate \dot{X} in terms of Y_N , okay, that is the problem.

Use finite difference approximations. For example,

$$\dot{x}(t) \approx \frac{x(t + \Delta t) - x(t)}{\Delta t} \Rightarrow \dot{y}_n \approx \frac{y_{n+1} - y_n}{\Delta t_n}$$

$$\Rightarrow y_{n+1} \approx y_n + \Delta t_n a[y_n, t_n]; n = 0, 1, 2, \dots \text{ with } y_0 = x_0$$

$$\text{and } \dot{y}_n = a[y_n, t_n] \quad (\text{given that } \dot{x}(t) = a[x(t), t])$$

Here $\Delta t_n; n = 0, 1, 2, \dots$ = algorithmic parameters.

Accuracy depends upon the choice of $\Delta t_n; n = 0, 1, 2, \dots$



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Now we could use finite difference approximation for example $X \dot{(t)}$ can be written using forward difference scheme, $X \dot{(t)}$ is approximately equal to $X(t + \Delta T) - X(t) / \Delta T$, so consequently I can write this as $Y_N \dot{=} Y_{N+1} - Y_N / \Delta T_N$, so from this I can derive now the equation for Y_{N+1} , which will be $Y_N + \Delta T_N \text{ into } Y_N \dot{}$, Y_N is nothing but $A(Y_N, T_N)$, where N runs from 0, 1, 2, 3, with $Y_{naught} = X_{naught}$ at $T = T_{naught}$. Now ΔT_N are the algorithmic parameter $\Delta T_1, \Delta T_2, \Delta T_3$ are the algorithmic parameters, if all of them are equal then ΔT is the only algorithmic parameter. Now the accuracy of this solution depends upon this choice of these algorithmic parameters ΔT_N , if ΔT_N are all equal the accuracy depends basically on the choice of ΔT .

Errors

Local discretization error: $l_{n+1} = x(t_{n+1}, x_n, t_n) - y_{n+1}$

Global discretization error: $e_{n+1} = x(t_{n+1}, x_0, t_0) - y_{n+1}$

Round-off error: R_{n+1} (due to the use of finite precision calculations)

Dynamical system modeling errors: does the algorithm correctly capture dynamical properties of systems (such as natural frequencies, free vibration amplitudes, energy conservation,...)?



Now we talk about errors, we call something on a local discretization error, this is $X(TN+1, XN, TN) - YN+1$ that means this is, I have moved from $T = TN$ to $T = TN+1$ to get $X(TN+1)$ and that is approximated as $YN + 1$, so this error is called local discretization scheme, that means we are basically moving from TN to $TN+1$. On the other hand if you move from T naught to $TN+1$ that means all the preceding steps up to $N+1$ step if you cover then we call this error as the global discretization error, there is other error called round off error which is due to finite precision calculations, so you do either double precision or single precision calculation, typically we do double precision calculations, so on a computer the digits get terminated so it is inevitable so there will be errors, that we call as $RN+1$. Of course there are other errors which we call as dynamical system modeling errors, for example does algorithm correctly capture dynamical properties of system like natural frequencies, frequency response functions, free vibration amplitudes, is the energy conserved suppose I am dealing with an undamped free vibration problem, is the energy conserved? So if there is any compromise on any of these issues, these can be grouped as dynamical system modeling errors.

How to formulate the integration algorithms to achieve acceptable accuracy? How to understand the nature of the errors?

$$\lim_{n \rightarrow \infty} \|e_n\| \rightarrow \begin{cases} 0? \\ c < \infty? \\ \infty? \end{cases}$$

How to select algorithmic parameters to achieve acceptable performance of the integrators?



What are the expectations from a good integrator?

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Now the basic question that we are looking for is how to formulate the integration algorithms to achieve acceptable accuracy, there's so many errors of different kinds so associated with that there is a definition of an accuracy so how to understand the nature of different errors, okay, and does this error as N tends to infinity norm of E_N , does it go to 0, or does it remain finite, or does it become unbounded, so at every time step certain error is made either because of truncating of, we are approximating the derivative by a finite difference approximation and there is a round off error, so consequently at every time step there will be an error, so how does this error committed at one step, how does it propagate to the future steps, so does it go to 0 or it remains bounded or does it become unbounded. So now how to select algorithmic parameters to achieve acceptable performance of the integrators, so what are the expectations from a good integrator, so these are the type of questions we want to now address.

Dynamical system modeling errors:

Consider scalar equation $\ddot{u} + \omega^2 u = 0; u(0) = u_0, \dot{u}(0) = \dot{u}_0$

Exact solution

$$u(t) = u_0 \cos \omega t + \frac{\dot{u}_0}{\omega} \sin \omega t = R \cos(\omega t - \theta)$$

$$R = \sqrt{u_0^2 + \left(\frac{\dot{u}_0}{\omega}\right)^2} \quad \& \quad \tan \theta = \frac{\dot{u}_0}{\omega u_0}$$

In the discrete approximation:

- Do we get amplitude of response to be constant?

Otherwise we get numerical dissipation or growth.



- Do we get the impulse response function correctly?

Is the distortion acceptable?

- Is the vibration energy conserved?

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Now let's spend some time on dynamical system modeling errors so that we understand what exactly is meant, so now let us consider the scalar equation of motion $\ddot{U} + \omega^2 U = 0$, so it is a single degree freedom system, natural frequency is ω and it starts with initial condition $U(0) = u_0$ and $\dot{U}(0) = \dot{u}_0$, we can solve this problem exactly and we know that this is the solution, we have an amplitude and FS that they are given by this, they are functions of initial conditions and system natural frequency. Now the question is suppose if I solve this equation using the discrete approximation, do we get amplitude of response to be constant, for example do we get the solution in this form where R is a constant, otherwise we get numerical dissipation or growth, if amplitude is not constant either it will decay or it will grow, so then that would mean that the algorithm has introduced some artificial dissipation mechanism into the system which is not there in the original equation of motion, then do we get the impulse response function correctly, is the distribution distortions acceptable, okay, what is acceptable distortion? Now is the vibration energy conserved, some of these questions are important, so answering these questions would enable us to discuss the dynamical system modeling errors.

Dynamical system modeling errors (continued):

Similarly, for the system

$$\ddot{u} + 2\eta\omega\dot{u} + \omega^2 u = P \exp(i\Omega t); u(0) = u_0, \dot{u}(0) = \dot{u}$$

are the properties of the frequency response curve preserved?

Similarly, for nonlinear systems we can pose questions on bifurcation characteristics.



We could also consider for example a damped harmonically driven oscillator and we know that in steady state this type of systems have certain well-known features, there is a resonance and where the resonance occurs, what is resonance amplitude, now what is the shape of the frequency response function so on and so forth, there are well known qualitative features associated with the response of the system. Now the question we can ask is does the discretized version of the solution process these well-known features or not, okay, so that is one. Similarly if there is a nonlinear term we are not discussed about nonlinear term, but we can think of adding say for example αU^3 here, now such systems display a pattern of bifurcations we will come to that later but at this stage it is suffice to observe that nonlinear systems have certain qualitative features in the associated with their behavior, and we can ask the question does the discretized version of the equation display the same type of qualitative behavior as the continuous version, okay, this type of issues can be grouped under the heading of dynamical system modeling errors.

Outline

- Mathematical preliminaries
- The integration schemes
 - Explicit/implicit
 - Single step/multi step
- Consistency
- Stability
- Accuracy
- Energy conservation



So what we are going to do is, there will be a few mathematical preliminaries that are needed to understand the questions and the answers that we will be discussing related to the properties of these integration schemes, and there are some set of terminologies we talked about implicit schemes, explicit scheme, single step method, multi-step methods, self-starting, and not self-starting, we talk about consistency of this, stability of these methods and we discussed inner accuracy, energy conservation properties, and so on and so forth, so what we will do is we will try to discuss these issues as we go along, so we'll start with some simple mathematical

Mathematical preliminaries-1

The O and o notations

• The meaning of $f(x)$ being $O[g(x)]$ as $x \rightarrow a$

• The function $f(x)$ is said to be $O[g(x)]$ as $x \rightarrow a$ if $\lim_{x \rightarrow a} \left| \frac{f(x)}{g(x)} \right| < \infty$

• The function $f(x)$ is said to be $o[g(x)]$ as $x \rightarrow a$ if $\lim_{x \rightarrow a} \left| \frac{f(x)}{g(x)} \right| \rightarrow 0$

$$f(x) = O[g(x)] \text{ as } x \rightarrow a$$



$$\forall \epsilon > 0 \ \& \ \delta > 0 \ \exists \ |f(x)| \leq M |g(x)| \ \forall \ |x - a| < \delta$$



preliminaries, we discussed this earlier in one of the lectures, we will be using this so-called gauge notations the O , and capital O and lowercase o notations, we say that $F(x)$ is of order $G(x)$ as X tends to A , if as X tends to A this ratio $F(x)/G(x)$ it remains finite, okay, and if this goes to 0 then we say that it is lowercase order $G(x)$ okay, the mathematical description is given here I will not get into these details I have provided it for sake of completion, but I will list it with few examples. Now let's consider this function A into X to the power of 7, BX cube + CX + D , we make a statement that this function is order X to the power of 7, as X tends to infinity, so how do you verify, you would divide this by X to the power of 7, okay and you can see that this goes to as X tends to infinity, this goes to A , right the first term will be A , second term will be B/X to the power of 4, C/X to the power of 6, D/X to the power of 7, so in the denominator as X tends to infinity all the terms go to 0 except the first term which is A , so we say that this statement is verified by checking this, similarly this function is order X to the power of 0 as X goes to 0, how do I check? You take extra 0, as X goes to 0 only D will remain, so this is finite, right, so this polynomial is order X to the power of 0.

Examples

$$\bullet ax^7 + bx^3 + cx + d \text{ is } O(x^7) \text{ as } x \rightarrow \infty \because \lim_{x \rightarrow \infty} \left| \frac{ax^7 + bx^3 + cx + d}{x^7} \right| \rightarrow a < \infty$$

$$\bullet ax^7 + bx^3 + cx + d \text{ is } O(x^0) \text{ as } x \rightarrow 0 \because \lim_{x \rightarrow 0} \left| \frac{ax^7 + bx^3 + cx + d}{x^0} \right| \rightarrow d < \infty$$

$$\bullet ax^7 \text{ is } O(x^7) \text{ as } x \rightarrow 0 \because \lim_{x \rightarrow 0} \left| \frac{ax^7}{x^7} \right| \rightarrow a < \infty$$

$$\bullet ax^7 \text{ is not } O(x^8) \text{ as } x \rightarrow 0 \because \lim_{x \rightarrow 0} \left| \frac{ax^7}{x^8} \right| \rightarrow \infty$$



Now A to the power of, X to the power of, A into X to the power of 7 is order X to the power of 7 as X goes to 0, how do you verify, you divide by X to the power of 7 and go take X to power of 0, I get A, which is finite, so there are a few more examples you can verify, you know, get a feel for what these terminologies mean. So I have a few more examples, let's quickly run

Examples


- $\sin(x)$ is $O(x)$ as $x \rightarrow 0$ $\because \lim_{x \rightarrow 0} \left| \frac{\sin(x)}{x} \right| \rightarrow 1 < \infty$

- $\sin(x^2)$ is $O(x^2)$ as $x \rightarrow 0$ $\because \lim_{x \rightarrow 0} \left| \frac{\sin(x^2)}{x^2} \right| \rightarrow 1 < \infty$

- $\cos(x)$ is $O(x^0)$ as $x \rightarrow 0$ $\because \lim_{x \rightarrow 0} \left| \frac{\cos(x)}{x^0} \right| \rightarrow 1 < \infty$

- $\sin(x)$ is $o(x^0) = o(1)$ as $x \rightarrow 0$ $\because \lim_{x \rightarrow 0} \left| \frac{\sin(x)}{x^0} \right| \rightarrow 0$

- $\cos(x)$ is $O(x^{\frac{1}{2}})$ as $x \rightarrow 0$ $\because \lim_{x \rightarrow 0} \left| \frac{\cos(x)}{x^{\frac{1}{2}}} \right| = \lim_{x \rightarrow 0} \left| \sqrt{x} \cos(x) \right| \rightarrow 0 < \infty$



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through this $\sin X$ is order X , as X goes to 0, why? You divide $\sin X/X$ and take X to 0 we know that this limit is 1, which is finite. Similarly $\sin X$ square is order X square by the same logic we come to this conclusion, $\cos X$ is order 1 as X goes to 0, because $\cos X/1$, as X goes to 0 is 1, and so on and so forth, so there are few more examples I'll leave it for you to verify.

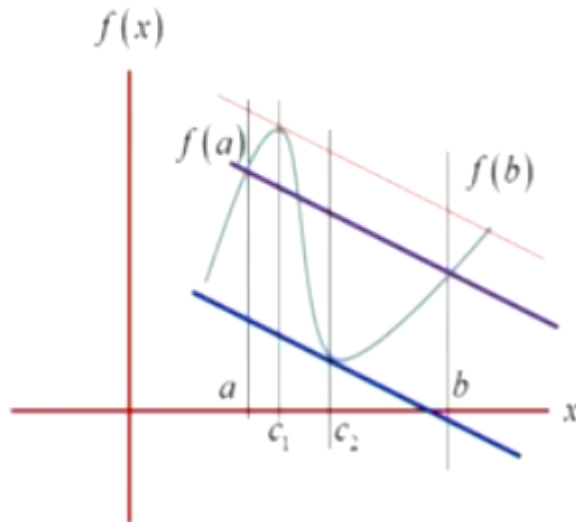
Mathematical preliminaries-2

Mean value theorem

Consider a function $f(x)$ to be continuous for $a \leq x \leq b$ and differentiable for $a < x < b$. According to the mean value theorem, there exists at least one c satisfying $a < c < b$ such that

$$\frac{df}{dx}(c) = \frac{f(b) - f(a)}{b - a}$$

$$\Rightarrow f(b) = f(a) + (b - a) \frac{df}{dx}(c)$$



There is one another mathematical preliminary that we would be needing, we should quickly recall what is the mean value theorem, now consider a function $F(x)$ to be continuous for X lying between A and B , and differentiable for, this is the closed interval, this is the open interval, it is differentiable in the open interval, then according to the mean value theorem there exists at least one C satisfying the condition that C lies between A and B such that DF/DX at C is exactly given by this $F(B) - F(A) / B - A$, that you can see here, this is my $F(x)$ and this is A and this is B , and you can see that at this point, and at this point, if you draw the curve DF/DX which is given by this, this will be parallel to the 2, you know this is the approximation so this will be parallel to this, which is a tangent to $F(x)$ at those points, so at C_1 and C_2 this is an exact representation, but of course for a given $F(x)$ we would not know where is that C , how many of them are there, whether there is you know where it is located we would not know.

Mathematical preliminaries-3

Taylor's series

Let f be a function of x with derivatives of all orders throughout an interval containing the point a . The Taylor series generated by f at $x = a$ is given by

$$\sum_{k=0}^{\infty} \frac{f^{(k)}(a)}{k!} (x-a)^k = f(a) + f'(a)(x-a) + \frac{f''(a)}{2!} (x-a)^2 + \dots + \frac{f^{(n)}(a)}{n!} (x-a)^n + \dots$$



Now Taylor's series is something that we are all familiar with, so let's quickly see the statement of some of the results associated with Taylor's series expansions, so again let F be a function of X with derivatives of all orders throughout an interval containing point A . The Taylor's series generated by F at $X = A$ is given by $F(A) + F'(A)(X - A) + \frac{F''(A)}{2!} (X - A)^2 + \dots$ and so on and so forth, this is the well-known Taylor's series. Now

Mathematical preliminaries-3

Taylor's polynomial

Let f be a function of x with derivatives of orders $n = 0, 1, 2, \dots, N$ throughout an interval containing the point a . Then for any $n \in [0, N]$ the Taylor polynomial of order n generated by f at $x = a$ is given by

$$P_n(x) = f(a) + f'(a)(x-a) + \frac{f''(a)}{2!}(x-a)^2 + \dots + \frac{f^{(n)}(a)}{n!}(x-a)^n.$$



if you truncate the Taylor's series at say the n th term we get what is known as the Taylor's polynomial, so that is other conditions remaining the same I write $P_N(x)$ as this, so this is known as Taylor's polynomial, okay.


Corollary to Taylor's theorem

If f has derivatives of all orders in an open interval I containing a , then for each positive integer n and for each x in I ,

$$f(x) = f(a) + f'(a)(x-a) + \frac{f''(a)}{2!}(x-a)^2 + \cdots + \frac{f^{(n)}(a)}{n!}(x-a)^n + R_n(x)$$

$$\text{where } R_n(x) = \frac{f^{(n+1)}(c)}{(n+1)!}(x-a)^{n+1} \text{ for some } c \text{ between } a \text{ and } x.$$

If $\lim_{n \rightarrow \infty} R_n(x) \rightarrow 0 \forall x \in I$, we say that the Taylor series generated by f at $x = a$ converges to f on I , and we write


$$f(x) = \sum_{n=0}^{\infty} \frac{f^{(n)}(a)}{n!}(x-a)^n$$

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Now the corollary to the Taylor's theorem, if F has derivatives of all orders in an open interval I containing A , then for each positive integer N and for each X in the interval I , $F(x)$ can be written as $F(A) + F'(A)(X-A) + \frac{F''(A)}{2!}(X-A)^2 + \cdots + \frac{F^{(N)}(A)}{N!}(X-A)^N + R_N(X)$ and so forth after n th term there is a remainder term, and this remainder is given by this for some C between A and X , this again we are using mean value theorem in writing this, now if this limit of this remainder term goes to 0, right for all X in I , we say that Taylor series generated by F at $X = A$ converges to F on I , and we write $F(x)$ is this, okay.

Mathematical preliminaries-4

Forward difference approximation to a derivative

$$f(x+h) = f(x) + hf'(x) + \frac{h^2}{2!} f''(x) + \frac{h^3}{3!} f'''(x) + \dots$$

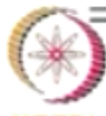
$$\Rightarrow f'(x) = \frac{f(x+h) - f(x)}{h} - \frac{h}{2!} f''(x) - \frac{h^2}{3!} f'''(x) + \dots$$

$$\Rightarrow f'(x) = \frac{f(x+h) - f(x)}{h} + O(h) \text{ as } h \rightarrow 0$$

Backward difference approximation to a derivative

$$f(x-h) = f(x) - hf'(x) + \frac{h^2}{2!} f''(x) - \frac{h^3}{3!} f'''(x) + \dots$$

$$\Rightarrow f'(x) = \frac{f(x) - f(x-h)}{h} + \frac{h}{2!} f''(x) - \frac{h^2}{3!} f'''(x) + \dots$$



$$\Rightarrow f'(x) = \frac{f(x) - f(x-h)}{h} + O(h) \text{ as } h \rightarrow 0$$

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Now we talked about forward difference, backward difference, and central difference, where I talked about finite difference, so some of the examples are forward difference, backward difference, central difference, so let's see quickly what it means, so let's consider a function $F(x)$ and I write the Taylor's expansion $F(x) + H$ is $F(x) + HF'(x) + \frac{H^2}{2!} F''(x) + \dots$ and so on and so forth. Now from this I can write, solve for $F'(x)$, $F'(x)$ will be given by $\frac{F(x+H) - F(x)}{H}$, so you are taking these, other term to the other side you are dividing by H therefore this becomes $H, \frac{H^2}{2!} + \frac{H^3}{3!}$ and so on and so forth. So this term is clearly of the order H , because if you divide by H and take $H \rightarrow 0$ this will be a finite quantity, right, so this we say that this is a forward difference approximation to $F'(x)$ at X , the backward difference approximation to derive that we consider instead of $F(x) + H$, I consider $F(x) - H$, so this will be $F(x) - HF'(x)$ and so on and so forth.

Again if I solve for $F'(x)$ I get this expression, and divided by, we have divided by H and we can see that these terms are of order H , as H goes to 0, so this approximation is known as backward difference approximation to $F'(x)$. To derive the central difference

Central difference approximation to a derivative

$$f(x+h) = f(x) + hf'(x) + \frac{h^2}{2!} f''(x) + \frac{h^3}{3!} f'''(x) + \dots$$

$$f(x-h) = f(x) - hf'(x) + \frac{h^2}{2!} f''(x) - \frac{h^3}{3!} f'''(x) + \dots$$

$$\Rightarrow f(x+h) - f(x-h) = 2hf'(x) + 2\frac{h^3}{3!} f'''(x) + \dots$$

$$\Rightarrow f'(x) = \frac{f(x+h) - f(x-h)}{2h} + O(h^2) \text{ as } h \rightarrow 0$$

Intuitively



Error is of $O(h)$ and we half step size \Rightarrow error gets halved.

Error is of $O(h^2)$ and we half step size \Rightarrow error gets quartered.

approximation what we do is we consider $F(x) + H$ which is this expansion, and also $F(x) - H$ which is this expansion, now I subtract these two, so if moment I subtract these 2, these 2 get cancelled, these 2 add up, I get $2H F'(x)$, and similarly this H^2 term will get cancelled, and I will get the next term will be of the $2H^3 / 3$ factorial so on and so forth. Now if I solve for $F'(x)$ from this, I get $F'(x)$ of X is $(F(x) + H - F(x) - H) / 2H$ + this term will be divided by H , so this will be order H^2 , so as H goes to 0, okay, so this is the central difference approximation for derivative of F at X . Intuitively we can see that if error is of the order H , and if we have H , that is the step size H the error gets halved, similarly if the order, error is of the order H^2 and if we half the step size the error will get quartered, okay so that is the advantage of order H^2 , okay.

Standard form

$$M\ddot{U}(t) + C\dot{U}(t) + KU(t) + R[\ddot{U}(t), \dot{U}(t), U(t), t] = F(t)$$

$U(0), \dot{U}(0)$ specified

$$\Rightarrow \dot{x} = a[x(t), t]; x(0) = x_0; 0 \leq t \leq t_f$$

Strategy: replace derivatives by finite difference approximations.


Introduce $0 < t_1 < t_2 < \dots < t_N = t_f$ & denote $y_n = x(t_n, 0, x_0)$

Forward difference approximation

$$\text{At time } = t, \dot{x}(t) = \frac{x(t + \Delta t) - x(t)}{\Delta t} = a[x(t), t]$$

$$\Rightarrow y_{n+1} = y_n + \Delta t \dot{y}_n = y_n + \Delta t a(y_n) + O(\Delta t)$$

Backward difference approximation



$$\text{At time } = t + \Delta t, \dot{x}(t + \Delta t) = \frac{x(t + \Delta t) - x(t)}{\Delta t} = a[x(t + \Delta t), t + \Delta t]$$

$$\Rightarrow y_{n+1} = y_n + \Delta t \dot{y}_{n+1} = y_n + \Delta t a[y_{n+1}] + O(\Delta t)$$

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Now let's return to the equilibrium equation in the standard form, we already seen that this equation can be written in this standard form in the state space, now what I will do is, I will replace this \dot{x} by finite difference approximation and see what we get, so we will consider a sequence of increasing time instant $0, T_1, T_2, \dots, T_N$, capital T_N is T_f which is a final time instant up to which we want to integrate this equation, and we denote y_N value of the system state at $T = T_N$ by starting at $T = 0$ with an initial condition x_0 , now for $\dot{x}(t)$ if I use forward difference approximation, $\dot{x}(t)$ will be written as $\frac{x(t + \Delta t) - x(t)}{\Delta t}$, and this must be equal to $A(x(t), t)$, so now if I solve for $x(t + \Delta t)$ which is y_{n+1} will be equal to y_n , that is $x(t) + \Delta t$ is on the other side, $\Delta t \dot{y}_n$, \dot{y}_n is $A(y_n)$, so I'll get y_{n+1} as $y_n + \Delta t A(y_n)$ and this order of approximation is order Δt , okay.

Now if we want now backward difference approximation we consider time instant $T + \Delta t$, and go back in time and I get $\dot{x}(t) + \Delta t$ is $\frac{x(t) - x(t - \Delta t)}{\Delta t}$, so this looks similar to this but here you must notice that I am writing this at time instant T , okay, $T + \Delta t$ is, I heard of the time at which I am writing this whereas here the T is lagging, okay $T + \Delta t$ is the current time and whereas T is the previous time instant. Now here again I can write y_{n+1} is $y_n + \Delta t$ this is important, this is \dot{y}_{n+1} whereas here it is \dot{y}_n , so this will be $y_n + \Delta t A(y_{n+1})$, whereas this is $A(y_n)$ and the order of accuracy is still order of Δt , the central difference scheme I can write this so again at time T , I write $\dot{x}(t)$ is

Central difference approximation

$$\text{At time } t, \dot{x}(t) = \frac{x(t + \Delta t) - x(t - \Delta t)}{2\Delta t} = a[x(t), t]$$

$$\Rightarrow y_{n+1} = y_{n-1} + 2\Delta t \dot{y}_n = y_{n-1} + 2\Delta t a(y_n) + O(\Delta t^2)$$

Trapezoidal rule

$$x(t) = \int_0^t \dot{x}(s) ds \Rightarrow x(t_{n+1}) = \int_0^{t_{n+1}} \dot{x}(s) ds = \int_0^{t_n} \dot{x}(s) ds + \int_{t_n}^{t_{n+1}} \dot{x}(s) ds$$

$$= y_n + 0.5\Delta t (\dot{y}_{n+1} + \dot{y}_n)$$

$$\Rightarrow y_{n+1} = y_n + 0.5\Delta t (\dot{y}_{n+1} + \dot{y}_n)$$

$$\Rightarrow y_{n+1} = y_n + 0.5\Delta t \{y_{n+1} + \Delta t a(y_{n+1}) + y_n + \Delta t a(y_n)\}$$



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$X(t + \Delta t) - X(t) - \Delta t/2 \Delta t$, this must be equal to $A(x(t), t)$, so I want to write for $X(t + \Delta t)$ I will get Y_{n+1} , this is $Y_n - 1, 2 \Delta t$ into $Y_n \dot{y}_n$, this is $Y_n \dot{y}_n$, so that is $Y_n - 1 + 2 \Delta t TA(Y_n)$ and this approximation is order Δt square, okay.

Now we can also develop another scheme which is slightly different from, logic is slightly different suppose $X(t)$ I write it as 0 to T , $X \dot{(s)} DS$, that's a definition of a derivative, so if you consider $T = T_{n+1}$, this will be 0 to T_{n+1} , $X \dot{(s)} DS$. This 0 to T_{n+1} I can write it as 0 to $T_n + T_n$ to T_{n+1} , so this first term is nothing but $X(T_n)$ and this is the increment. For this second term I will use the trapezoidal rule of integration, so I will therefore I will get this as Y_{n+1} as $Y_n + 1/2$ of Δt , $Y_n \dot{y}_{n+1} + Y_n \dot{y}_n$, okay, so from this I get this as the approximation. Now for Y_{n+1} , $Y \dot{y}_{n+1}$, I will write $A(Y_{n+1})$, and $Y_n \dot{y}_n$ I'll write it as $Y_n + \Delta t TA(Y_n)$, so this approximation is known as the approximation based on trapezoidal rule.

Forward difference approximation

$$y_{n+1} = y_n + \Delta t \dot{y}_n = y_n + \Delta t a(y_n) + O(\Delta t)$$

Backward difference approximation

$$y_{n+1} = y_n + \Delta t \dot{y}_{n+1} = y_n + \Delta t a[y_{n+1}] + O(\Delta t)$$


Central difference approximation

$$y_{n+1} = y_{n-1} + 2\Delta t \dot{y}_n = y_{n-1} + 2\Delta t a(y_n) + O(\Delta t^2)$$

Trapezoidal rule

$$y_{n+1} = y_n + 0.5\Delta t \{y_{n+1} + \Delta t a(y_{n+1}) + y_n + \Delta t a(y_n)\}$$

Generic form

$$y_{n+1} = \alpha_1 y_n + \alpha_2 y_{n-1} + \dots + \alpha_m y_{n+1-m} + \Delta t [\beta_0 \dot{y}_{n+1} + \beta_1 \dot{y}_n + \dots + \beta_k \dot{y}_{n+1-k}]$$


Now we can summarize all this, so in the forward difference scheme I had this representation in backward different scheme I had this representation, in central difference I had this, in trapezoidal rule I had this. Now a generic form based on this we can see that a generic form can be written as $y_{n+1} = \alpha_1 y_n + \alpha_2 y_{n-1} + \dots + \alpha_m y_{n+1-m} + \Delta t [\beta_0 \dot{y}_{n+1} + \beta_1 \dot{y}_n + \dots + \beta_k \dot{y}_{n+1-k}]$, so on and so forth up to the K-th term. This is a general form into the, all these schemes will fit into these by selecting alpha 1, alpha 2, etcetera, beta naught, beta 1 etcetera in a suitable manner I can recover these schemes. Let's consider the generic form again, you look at the term

Generic form

$$y_{n+1} = \alpha_1 y_n + \alpha_2 y_{n-1} + \dots + \alpha_m y_{n+1-m} + \Delta [\beta_0 \dot{y}_{n+1} + \beta_1 \dot{y}_n + \dots + \beta_k \dot{y}_{n+1-k}]$$

Definitions

- $\beta_0 \neq 0 \Rightarrow y_{n+1}$ depends upon derivative of the state at t_{n+1} , that is, upon \dot{y}_{n+1} .
The scheme is said to be implicit. Other wise the scheme is said to be explicit.
- If $\alpha_2 = \alpha_3 = \dots = \alpha_m = 0$, & $\beta_2 = \beta_3 = \dots = \beta_k = 0$, the scheme is said to be a single step scheme; otherwise it is called multi-step scheme.
- Scheme is said to be self starting if y_n for $n < 0$ does not enter the calculations.



beta naught, so I am writing $Y_{N+1} = Y$ at $T = T_{N+1}$ and this involves the derivative of the state at $N+1$, if β_0 is not 0, okay if β_0 is not 0 therefore Y_{N+1} plus depends upon derivatives of the state at T_{N+1} that is upon \dot{Y}_{N+1} , so such schemes are known as implicit schemes, okay, otherwise if β_0 is 0 then the scheme is said to be explicit.

Now if we now consider $\alpha_2, \alpha_3, \dots, \alpha_m$ as 0, and β_2 up to β_m are 0, then we say that the scheme is a single step scheme, otherwise it is called multi-step scheme. Now the scheme is set to be self-starting if Y_N for $N < 0$ does not enter the calculations, okay, right, so if I write this for N this term is a previous step, okay, suppose if $N = 0$, this will be Y_N and this is $\alpha_1 Y_N$, there is no problem, but in certain schemes you will soon see that I want to start with $N+1 = 0$ and this I will be needing Y of $-M$, and such schemes are said to be not self-starting okay we need to see that, so let's quickly see in this scheme of things how does

Forward difference approximation

$$y_{n+1} = y_n + \Delta t \dot{y}_n = y_n + \Delta t a(y_n) + O(\Delta t)$$

Backward difference approximation

$$y_{n+1} = y_n + \Delta t \dot{y}_{n+1} = y_n + \Delta t a[y_{n+1}] + O(\Delta t)$$

Central difference approximation

$$y_{n+1} = y_{n-1} + 2\Delta t \dot{y}_n = y_{n-1} + 2\Delta t a(y_n) + O(\Delta t^2)$$

Trapezoidal rule

$$y_{n+1} = y_n + 0.5\Delta t \{y_{n+1} + \Delta t a(y_{n+1}) + y_n + \Delta t a(y_n)\}$$

Generic form

$$y_{n+1} = \alpha_1 y_n + \alpha_2 y_{n-1} + \dots + \alpha_m y_{n-1-m} + \Delta t [\beta_0 \dot{y}_{n+1} + \beta_1 \dot{y}_n + \dots + \beta_k \dot{y}_{n-1-k}]$$

Forward difference approximation: single step, explicit, self-starting.

Backward difference approximation: single step, implicit, self-starting.

Central difference approximation: multistep, explicit, not self-starting.

Trapezoidal rule: single step, implicit, self-starting.

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this different classification schemes can be viewed as, suppose if you now consider forward difference approximation which is given by this, now you can see that this is a single step explicit self-starting scheme okay, explicit because y_{n+1} plus, we have y_{n+1} here and there is no derivative of y_{n+1} on the other side, backward difference scheme is again single step implicit, it is implicit self-starting okay, because you see here y_{n+1} is here $A(y_{n+1})$ is nothing but y_{n+1} , derivative of y_{n+1} so this is implicit, backward scheme is implicit. Similarly central difference approximation is, it is a multi-step method it is explicit, and it is not a self-starting scheme because here y_{n-1} you will see that in the due course, for example for $N = 0$, this will be y_N and I will be needing y_{-1} , and y_{-1} is a hypothetical quantity which is not there as a part of definition of the original problems of mechanics, problem of mechanics, so this is not a self-starting scheme and we need to devise some special methods to start the solution.

Similarly trapezoidal rule is single step implicit and it is self-starting, okay, why implicit, because I have $A(y_{n+1})$ here which is y_{n+1} dot, okay so if system is non-linear you can see that in implicit schemes you need to solve a times every time step an algebraic non-linear equation okay, so the implicit schemes that way demand computational efforts, especially if system is non-linear, if system is linear we can take these terms to the left side and rearrange the terms which is simply straight forward, so the difference between implicit scheme and explicit scheme will be strongly felt in computational effort for non-linear systems.

Remarks

- $t_0 = 0 < t_1 < t_2 < \dots < t_N = t_f$
- $t_n = n\Delta t$ [constant step size]
- System states: $U(t), \dot{U}(t), \ddot{U}(t)$
- Assume: System states at $t = t_n$ are known. To find system states at $t = t_{n+1}$.
Integration algorithms essentially achieve this.
- Computation effort is proportional to number of time steps to advance solution from $t = 0$ to $t = t_f$. The step size, therefore, need not be smaller than what is essential. We need to be concerned about
 - Growth of errors (stability) and
 - Accuracy of the solution.
 - Undamped free vibration of a sdof system:



Check for amplitude

Frequency distortions

Okay, let's make some observations and remarks so we have discretized time T naught to T_f in terms of $0, T_1, T_2, T_N$ which is a non-decreasing sequence of, actually increasing sequence of time instance, if we now take T_N to be $N \Delta T$, we say that we have a constant step size, okay, now system states are $U(t), \dot{U}(t)$ and $\ddot{U}(t)$ in our calculations, now if we assume that system states at $T = T_N$ are known and that is what we assume then the problem on hand is to find system states at $T = T_{N+1}$, the integration algorithms essentially achieve this, so these are known at time marching techniques, so we move from T_N to T_{N+1} and we want to take state from T_N to T_{N+1} , so these are called time marching techniques.

Now the computation effort is proportional to the number of time steps, okay to advance the solution from T to 0 to T to T_f , therefore the step size need not be smaller than what is essential they say what is the meaning of something being essential, it is something with accuracy basically, so what we need to be concerned about, we need to be concerned about growth of errors, does error committed at a time steps ΔT and grow as time advances, if it grows we say that the solutions are unstable, the scheme is unstable otherwise it is, if it remains constant we say it is stable, if it goes to 0 we say that it is as impractically stable, the accuracy of the solution step, if the errors do not grow, it does not mean that we get accurate answers, okay, how to judge accuracy? That is a different issue, now for example for undamped free vibration of a single degree freedom system we can check for amplitude, amplitude should remain constant and frequency distortions must not be there, we know that frequency let's say for example square root K/M do we get that square root K/M in numerical simulations or not.

Remarks (continued)

- The time integration method is the most generally applicable method to solve equilibrium equations:

For linear systems, the solution does not require transformation to natural coordinates. This enables treatment of general class of viscous damping models without stipulating damping to be classical. On the other hand, the method requires that damping be specified in terms of the C matrix and not in terms of modal damping ratios. Procedures to derive C matrix in terms of specified modal damping ratios have been discussed in this course. The excitation could be periodic, steady state aperiodic, or transient in nature.



The method remains applicable even when governing equations are nonlinear in nature.

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The time integration method is the most generally applicable method to solve equilibrium equations, we have talked about frequency response function, based methods, a dynamic stiffness, and so on and so forth, they are valid only for linear systems and of course there are additional requirements that system should reach harmonic steady-state, but here the system can be nonlinear, the excitations could be transient, this method remains applicable. Now for linear systems the solution actually does not require transformation to natural coordinates, see for linear system we can do, we can find natural frequencies, mode shapes, and uncouple the equation we have that option, but if you are trying to integrate the equation numerically it is not needed to actually perform the uncoupling of equations of motion, if you can do it, it helps but it is not essential, so this would mean that we have greater flexibility in modeling damping, see we have seen that if damping is classical there are many advantages in doing a more analysis based on mode superposition, but if you are doing direct integration there is no special requirement on what should be the damping matrix, because you can directly integrate.

Now but in practice we prefer to specify damping in terms of modal ratios, in that case damping will be specified in terms of as formulation which employs normal modes, natural coordinates and normal modes, so if you intend to use direct integration in such situations you have to formulate the C matrix from the known information about modal damping ratios, so we have discussed how to do that in the previous class. As I already said the method remains applicable even when equations of motions are nonlinear.

Remarks (continued)

For linear systems, the size of the model (dof-s) depend upon the details of mesh used in spatial discretization. These details needs to be chosen such that the system behavior is well represented over the frequency range over which excitations have significant power. If Ω_{\max} is the highest frequency present in the excitations, then all the modes present in the frequency range up to about $1.25\Omega_{\max}$ needs to be correctly captured. If the structure has, say, r modes in frequency range up to $1.25\Omega_{\max}$, then the mesh details should be such that the model has at least $10r$ dof-s.



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Now let's look at modeling of linear multi degree freedom systems, so how many degrees of freedom should be included in our model, we will discuss this in again at a later stage but we can start asking these questions at this stage, now the size of the model that is number of degrees of freedom actually depend on details of mesh used in the spatial discretization, now these details need to be chosen such that the system behavior is represented with acceptable accuracy over a given frequency range, what is the frequency range that we should select? We should look at excitation, suppose you are dealing with say earthquake like excitation the frequency range can be up to say about 20 to 30 Hertz from low frequency to up to that frequency, wind it could be 0 to 2 Hertz or 3 Hertz, wave also in the same region, so if you are performing say seismic response analysis of engineering structure you should ensure that say within the frequency range of say 0 to 20 Hertz whatever are the natural modes that the structure possess all of them should be modeled accurately, so we have seen that if you want to capture first say 5 modes in a model, you should have about 50 degrees of freedom in your model, that means the spatial discretization should be fine enough so that you get a model with 50 degrees of freedom so that at least one tenth of the natural frequencies will be computationally trustworthy, so that would mean if ω_{\max} is the highest frequency we will say that the discretization scheme should be such that all the modes that lie in frequency range up to $1.25\omega_{\max}$ need to be captured well, so the mesh details should be such that the model has at least $10R$ degrees of freedom, where R is the number of degrees of freedom, the R is the number of modes that you expect the structure to have in frequency range up to $1.25\omega_{\max}$, a consequence of this is that when you are using direct integration you will always

Remarks (continued)

This invariably means that there would be a large number of higher order modes that are present in the model (with frequencies beyond Ω_{\max}) which however do not contribute significantly to the response.

It is desirable that the discretization scheme used should have inherent capability to (numerically) dissipate the higher order spurious modes and yet the same time not distort the lower order modes which contribute significantly to the response.



be dealing with models which have, which has spurious higher-order modes, suppose you are making a model with 100 degrees of freedom we know that the first 10 modes are likely to contribute to the response, and modes from 10 to 100 are the higher order spurious modes.

Now it is desirable that the discretization scheme that is the time discretization scheme should have some inherent capability to numerically dissipate the higher order spurious modes, but not affecting the genuine lower order modes which contributes significantly to the response, so this would mean that we look for certain numerical dissipation characteristics in our integration schemes when we formulate the time integration schemes, so what is desirable is that the lower modes should not be numerically dissipated, but the higher spurious mode should be numerically dissipated, okay, we will see more about that, but this is one of the concern that we need to appreciate at the outside.

Discussion on following methods

- Explicit method with first order accuracy

Forward Euler

- Implicit method with first order accuracy

Backward Euler

- Explicit method with second order accuracy

Central difference

- Implicit method with second order accuracy

Newmark's family of methods

HHT- α method and generalization

- Explicit-Implicit methods

HHT- α with operator splitting



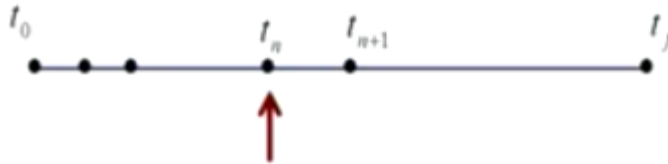
So what we will do now is will take up discussions on few methods I propose to discuss the following method, the forward Euler method, the backward Euler method, the central difference method, and there are methods known as Newmark's family of methods, and HHT alpha method, and so on and so forth, so we will see the development of these methods and as we go along we will see what motivates, what are the motivations to develop different schemes after getting, for example backward Euler scheme what is the need to go for central difference method, and what is the need to go to Newmark's family of methods when you already have done central difference method and so on and so forth. So the questions will be on stability, accuracy, dissipation of higher or spurious modes and so on and so forth, methods being implicit or explicit, these issues also will come up.

Strategy

- Development of basic formulary
- Pseudocode for implementation
- Analysis of the method
- Illustrative examples
- Discussion on relative merits

So what we, the strategy we will take is, we will develop the basic formulary for each of these schemes, and I will provide a Pseudocode for implementation, then we will analyze the method for its, how the errors behave in each, the specific method and then we will illustrate each of these methods with a few examples and we'll conclude by discussing the relative merits of different methods, so this is a scheme of things that we will follow.

Forward Euler Method



$$M\ddot{U}(t) + C\dot{U}(t) + KU(t) = F(t)$$

$$U(0) = U_0; \dot{U}(0) = \dot{U}_0; 0 \leq t \leq t_f$$

$$\left. \begin{aligned} \dot{U}(t) &= \frac{U(t+\Delta t) - U(t)}{\Delta t} \Rightarrow U_{n+1} = \Delta t \dot{U}_n + U_n \\ \ddot{U}(t) &= \frac{\dot{U}(t+\Delta t) - \dot{U}(t)}{\Delta t} \Rightarrow \dot{U}_{n+1} = \Delta t \ddot{U}_n + \dot{U}_n \end{aligned} \right\} \text{This is an explicit scheme}$$

⇒ Condition for equilibrium at t_{n+1} is given by

$$M\ddot{U}_{n+1} + C(\Delta t \ddot{U}_n + \dot{U}_n) + K(\Delta t \dot{U}_n + U_n) = F_n$$

$$\Rightarrow \ddot{U}_{n+1} = -M^{-1} [C(\Delta t \ddot{U}_n + \dot{U}_n) + K(\Delta t \dot{U}_n + U_n) - F_n]$$

So let me start with the discussion on forward Euler method, so this is a time axis T naught is here, T_f is a final time instant which is here, so let's the equation of equilibrium is MU double dot + U dot + $KU = F(t)$ at time T , these are the initial conditions. Now at time T , I will

approximate the velocity $\dot{U}(t)$ using forward difference scheme, which is $U(t) + \Delta T - U(t) \Delta T$, so from this I can get U_{N+1} which is $U(t) + \Delta T$ as ΔT into \dot{U} , that is $U_{N+1} - U_N$, a similar approximation I can make for acceleration also, so that will be $\dot{U}(t+\Delta t) - \dot{U}(t) / \Delta T$, where $\dot{U}(N+1)$ is obtained as ΔT , $\ddot{U}_N + \dot{U}_N$, so you can see here this is an explicit scheme, because when I am writing the state at $N+1$ I do not need acceleration at $N+1$, okay, now so let us consider the condition for equilibrium at T_{N+1} , so this is written as $M\ddot{U}_{N+1} + C\dot{U}_{N+1} + KU_{N+1} = F_{N+1}$ I will use this, okay this is this, then for U_{N+1} I will use this, so this is this, this is equal to F_N where $F_1 = F(t_n)$. Now I will rearrange these terms what is not known is \ddot{U}_{N+1} and that is obtained in terms of the remaining terms like this.

Implementation of the forward Euler Method

$$(1) n = 0; t = 0; \text{ Input } U_0 \text{ \& } \dot{U}_0$$

$$\ddot{U}_0 = -M^{-1} [C\dot{U}_0 + KU_0 - F_0]$$

$$(2) \ddot{U}_{n+1} = -M^{-1} [C(\Delta\ddot{U}_n + \dot{U}_n) + K(\Delta\dot{U}_n + U_n) - F_n]$$

$$(3) \dot{U}_{n+1} = \Delta\ddot{U}_n + \dot{U}_n$$

$$(4) U_{n+1} = \Delta\dot{U}_n + U_n$$

$$(5) n \rightarrow n+1$$

$$(6) \text{ If } n\Delta t > t_f, \text{ stop; else go to (2)}$$



So how do we implement the method you can see here the scheme is very clear, I have to bank on this equation, this equation, and the final equation here, so I will start with $T = 0, N = 0$, we will input the initial condition U naught and \dot{U} naught, I will also need the initial acceleration, I will obtain it from the equation of motion, then I start with this equation, \ddot{U}_{N+1} which is given by this, so here \ddot{U}_N, \dot{U}_N etcetera are known, for example when $N = 0$ this will be \ddot{U}_1 , this will be \dot{U}_0 and U_0 , and they are already specified here, \dot{U}_0 and U_0 are given initial conditions and \dot{U}_0 is obtained from the governing equilibrium equation, so this is right. Then I'll find the velocity and the displacement, then I'll increment N and if $N\Delta T$ is more than T_f I'll stop, otherwise I'll go to 2, so this is the simple-minded outline of how to implement the forward difference scheme, but if you carefully look at this it is not necessary to invert M matrix at every time T , you need not have to multiply M inverse and C at every time T and so on and so forth, so we can refine this a bit so what I will do is I will calculate these matrices inverse and this product outside the loop, they need to be done only once, we need not do every time T , so if you do that I get a more usable implementation scheme, so I will input

Implementation of the forward Euler Method

(1) Input K, M, C matrices; Δt ; $F_n = F(n\Delta t)$, U_0 & \dot{U}_0

(2) $A = M^{-1}$; $B = AC$; $D = AK$

(3) $n = 0$; $t = 0$; Input U_0 & \dot{U}_0

$$\ddot{U}_0 = -(B\dot{U}_0 + DU_0 - AF_0);$$

(4) $\ddot{U}_{n+1} = -B(\Delta t \ddot{U}_n + \dot{U}_n) - D(\Delta t \dot{U}_n + U_n) + AF_n$

(5) $\dot{U}_{n+1} = \Delta t \ddot{U}_n + \dot{U}_n$

(6) $U_{n+1} = \Delta t \dot{U}_n + U_n$

(7) $n \rightarrow n+1$

(8) If $n\Delta t > t_f$, stop; else go to (4)



KMC matrices and delta T there is some algorithmic parameter and we will also store all the excitation and then the initial conditions, so I will define A as M inverse, B as A into C, C is damping, D is A into K.

Now we will start with $N = 0$, and we will accept this U naught and U naught dot form U naught double dot, so I am not inverting any of these matrices nor I am multiplying any matrix now, so U_{n+1} double dot is given by this, I get similarly velocity and displacement, and I will increment time and if I cross the final time instant I will stop, otherwise I will restart with this time, so the most of the calculation gets done in the steps 4 to 6, and I am not repeating any calculation, if I can avoid I'll avoided all that, okay, so this is the forward Euler forward difference scheme, okay, it is logically simple, so what we can do now is we can think of asking

Forward Euler Method : stability analysis

$$\ddot{x} + 2\eta\dot{x} + \omega^2 x = f(t) \Rightarrow$$

$$\dot{U}_{n+1} = \Delta t \ddot{U}_n + \dot{U}_n = \Delta t (-2\eta\omega \dot{U}_n - \omega^2 U_n + f_n) + \dot{U}_n$$

$$U_{n+1} = \Delta t \dot{U}_n + U_n$$

$$\Rightarrow \begin{pmatrix} U_{n+1} \\ \dot{U}_{n+1} \end{pmatrix} = \begin{bmatrix} 1 & \Delta t \\ -\omega^2 \Delta t & 1 - 2\eta\omega \Delta t \end{bmatrix} \begin{pmatrix} U_n \\ \dot{U}_n \end{pmatrix} + \begin{pmatrix} 0 \\ \Delta t f_n \end{pmatrix}$$

$$\Rightarrow Y_{n+1} = AY_n + L_n$$

$$Y_n \rightarrow Y_n + \Gamma_n$$

$$\Rightarrow Y_{n+1} + \Gamma_{n+1} = AY_n + A\Gamma_n + L_n$$

$$\Rightarrow \Gamma_{n+1} = A\Gamma_n$$



how does errors behave, when I apply this scheme to analysis of simple systems.

Now for purpose of illustration I will consider a single degree freedom system under some excitation $F(t)$, now this is the scheme I will get using forward difference scheme for this problem I will get this is the scheme, okay, now this can be written as capital Y_{N+1} as $AY_N + L_N$ okay, where A is this matrix, okay, now suppose at the N -th step the state that is U_{N+1} and \dot{U}_{N+1} is contaminated by noise γ_N , now the question is how does γ_N behave? So I will substitute this into this equation so Y_{N+1} will be $Y_{N+1} + \gamma_{N+1} = AY_N + A\gamma_N + L_N$, so now Y_{N+1} is solution to this equation, therefore this, this and this cancel out, they are equal, the sum of these two is equal to this, so that gets out of reckoning, so the error is γ_{N+1} is $A\gamma_N$, so this is the equation for evolution of the error γ , so we will digress a bit now, will return to that shortly, but let us examine the

Digression

Consider the **scalar** equation $x_{n+1} = ax_n$ with $x_0 \neq 0$ specified.

\Rightarrow

$$x_1 = ax_0$$

$$x_2 = ax_1 = a^2 x_0$$

\vdots

$$x_n = ax_{n-1} = a^n x_0$$

Clearly

$$\lim x_n \left. \begin{array}{l} \rightarrow 0 \text{ if } |a| < 1 \\ = x_0 \text{ if } |a| = 1 \\ \rightarrow \infty \text{ if } |a| > 1 \end{array} \right\}$$




nature of this kind of finite difference equations suppose you consider a scalar equation $x_{n+1} = ax_n$, and we start with some nonzero initial conditions, so x_1 will be ax_0 , x_2 will be $a^2 x_0$ which is A square x_0 , and x_n will be A to the power of n x_0 , now if I am interested in knowing what happens to x_n as n tends to infinity, we can easily see here that this function will go to 0, if modulus of A is less than 1, suppose A is 0.1, A square will be 0.01, A to the power of 3 will be 0.001 and so on and so forth, A to the power of 10 will be 10 to the power of -10, so on and so forth, so this is the condition.

Now if A is 1, +1 or -1, x_n will stay at x_0 , as n tends to infinity, okay, and similarly if A is greater than 1, suppose A is 2, initially it will be $2x_0$, then $4x_0$, then $16x_0$ and so on and so forth, it goes to infinity as n tends to infinity, so the behavior of this x_n as n tends to infinity is crucially governed by the value of A , if the absolute value of A is less than 1, x_n goes to 0 as n tends to infinity, this is scalar equation. Suppose now you

Let us now consider the $s \times 1$ **vector** equation $x_{n+1} = Ax_n$ with $x_0 \neq 0$ specified. Here A is a $s \times s$ matrix.

\Rightarrow

$$x_1 = Ax_0$$

$$x_2 = Ax_1 = A^2x_0$$

\vdots

$$x_n = Ax_{n-1} = A^n x_0$$

Let us introduce the transformation $x_n = \Phi z_n$

$$\Rightarrow \Phi z_{n+1} = A\Phi z_n$$

Let Φ be such that $\Phi' \Phi = I$ & $\Phi' A \Phi = \text{Diag}[\lambda_i]$



We can select Φ by solving the eigen value problem associated with matrix A .

consider S cross 1 vector equation, suppose this is $x_{n+1} = Ax_n$, where A is S cross S matrix, okay. Now x_1 is Ax_0 , x_2 is Ax_1 which is A^2x_0 , similarly x_n will be $A^n x_0$. Now let's do the following, let us introduce a transformation $x_n = \Phi z_n$, so this equation for x_{n+1} will be $\Phi z_{n+1} = A\Phi z_n$.

Now let Φ be such that $\Phi' \Phi = I$, and $\Phi' A \Phi$ is a diagonal matrix, say if A is such that this is possible, how do we select, we can select Φ by solving the eigenvalue problem associated with A , that we have seen in few lectures how to do that, now suppose A, B such that this is possible, then I can write $x_{n+1} = A x_n$ and pre

$$\begin{aligned}
x_n &= \Phi z_n \\
\Rightarrow \Phi z_{n+1} &= A \Phi z_n \\
\Rightarrow \Phi' \Phi z_{n+1} &= \Phi' A \Phi z_n \Rightarrow z_{n+1} = \text{Diag}[\lambda_k] z_n \\
\Rightarrow z_{n+1}^k &= \lambda_k z_n^k; k = 1, 2, \dots, s \\
\Rightarrow z_{n+1}^k &= \lambda_k^n z_0^k; k = 1, 2, \dots, s \\
\Rightarrow x_n^j &= \sum_{k=1}^s \Phi_{jk} \lambda_k^n z_0^k \text{ with } z_0 = \Phi' x_0
\end{aligned}$$

We are interested in whether or not $\lim_{n \rightarrow \infty} |x_n^j| \rightarrow 0$ for $j = 1, 2, \dots, s$

Clearly,

$$\max_{1 \leq k \leq s} |\lambda_k| < 1 \Rightarrow \lim_{n \rightarrow \infty} |x_n^j| \rightarrow 0 \text{ for } j = 1, 2, \dots, s$$



That is, the behavior of $\lim_{n \rightarrow \infty} |x_n^j|$ for $j = 1, 2, \dots, s$ controlled by the highest modulus of the eigenvalues of A .

multiply by phi transpose I get this equation, now since phi transpose phi is I, I get Z_{n+1} and phi transpose A phi is a diagonal matrix of lambda I, I get this, okay, so Z is a S cross 1 vector therefore I can write the K-th element of that, Z_{n+1}^k as $\lambda_k^n z_0^k$ where K runs from 1 to S, so this is the equation I get, Z_{n+1}^k , now the behavior of this individual Z as K tends to infinity, depends on absolute value of lambda K, the K-th eigenvalue, right, now if you are interested in J-th component of your vector X, that is given by this summation, okay, so the behavior of this as N tends to infinity crucially depends on the highest eigenvalue that if you rank order this lambda K depending on the absolute value of its, that is the absolute value of lambda K, we are interested in, if you are interested in knowing what happens to this modulus of X_n^j as N tends to infinity, for this to go to 0 we require that the maximum value of this lambda K must less than 1, okay, because each 1 is a scalar equation, for each scalar equation to go to 0, the each of the eigenvalue, absolute value should be less than 1, so if the highest eigenvalue is a modulus is less than 1, then X_n^j will go to 0, as N tends to infinity, so therefore if you are interested in behavior of X_n^j as N tends to infinity, that is controlled by the highest modulus of the eigenvalues of A, okay.

Alternatively, consider

$$x_n = Ax_{n-1} = A^n x_0$$

Let us seek solution in the form $x_n = \alpha^n x_0$

Here α is scalar which is in general complex valued.

$$x_n = \alpha^n x_0 \Rightarrow x_{n+1} = \alpha^{n+1} x_0$$

Consider the equation $x_{n+1} = Ax_n = A^n x_0$

$$\alpha^{n+1} x_0 = A\alpha^n x_0 \Rightarrow Ax_0 = \alpha x_0$$

For nontrivial solutions $|A - \alpha I| = 0$

$$\Rightarrow \alpha_i = \alpha_{0i} \exp(i\theta_i)$$

Condition for $\lim_{n \rightarrow \infty} |x_n^j| \rightarrow 0$ for $j = 1, 2, \dots, s$ is given by $\max_{1 \leq i \leq s} |\alpha_i| < 1$



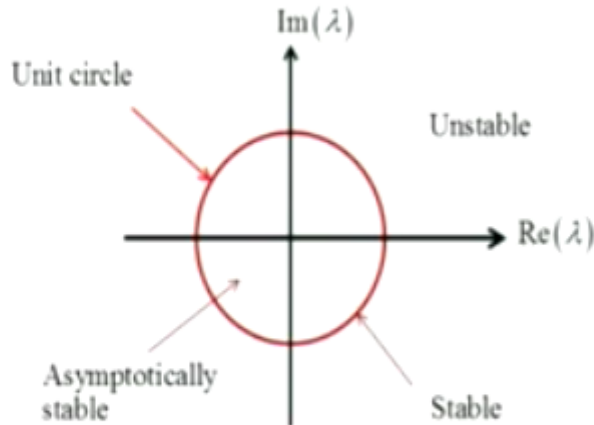
By definition $\max_{1 \leq i \leq s} |\alpha_i| = \rho(A)$ is called the **spectral radius** of A .

Now alternatively we can also consider x_n as Ax_{n-1} into A into x_{n-1} , I can write it as A to the power of n , x_n is $\alpha^n x_0$, now if we seek the solution now of the form x_n is $\alpha^n x_0$, suppose if you seek this solution, for some value of α such a solution may be possible, for which value of α this is possible we have to see, this α could be scalar, the scalar which can, in general be complex value, so now you substitute this into this equation, I get x_n is $\alpha^n x_0$, therefore x_{n+1} is $\alpha^{n+1} x_0$. Now if you consider this equation $x_{n+1} = Ax_n$, A to the power of x_0 and make these substitutions I get $\alpha^{n+1} x_0 = A\alpha^n x_0$, so from this I get Ax_0 is αx_0 , so this would mean for non-trivial solutions the determinant of $A - \alpha I$ must be equal to 0, and if we represent the roots of this equation which are the eigenvalues of A , suppose i -th root is written as $\alpha_{0i} \exp(i\theta_i)$, this is a complex number so I can always represent like this.

The condition for $|x_n^j|$ modulus of that as n tends to infinity to go to 0 is given by the condition that the maximum value of, absolute value of α_i must be less than 1, so that would mean actually this quantity which is a maximum value of modulus of the eigenvalue for i running from 1 to s is known as spectral radius of A , okay so what we are asking is the spectral radius

$$\max_{1 \leq k \leq s} |\lambda_k| < 1 \Rightarrow \lim_{n \rightarrow \infty} |x_n^j| \rightarrow 0 \text{ for } j = 1, 2, \dots, s$$

\Rightarrow The roots of the characteristic equation must lie within the unit circle in the complex plane.



We do not need the value of the eigenvalues.

We need to only ascertain if all the roots of the characteristic equation lie within the unit circle in the complex plane.

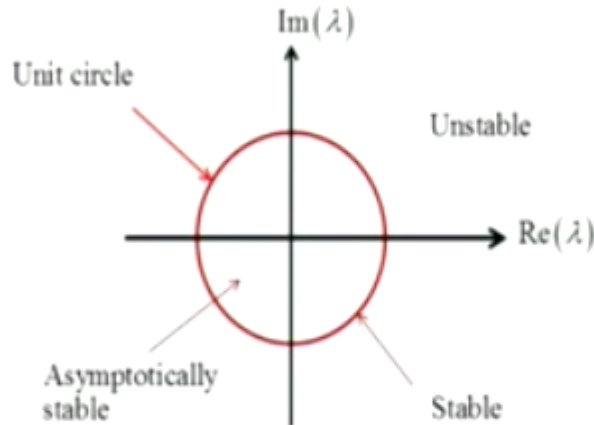
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of A must be less than 1 so that would mean if you look at the eigenvalue in the complex plane we have real part here, imaginary part here, and this is the so-called unit circle, okay it has radius equal to 1, what we want is the root should be inside this unit circle for stability asymptotic stability, if it is right on the unit circle the errors don't grow, but it is stable, but if it is outside the unit circle the errors would grow, okay, so this is what we need to verify if you are interested in studying the growth of errors.

One more thing that we should notice here is the only question we need to answer is whether roots lie within unit circle or not, we are not so much interested in knowing the absolute value of the route, we are simply interested in knowing a qualitative feature associated with the roots. So we do not need the value of eigenvalues, we need to only ascertain if all the roots of the characteristic equation lie within the unit circle in the complex plane, given that we are asking a

$$\max_{1 \leq k \leq s} |\lambda_k| < 1 \Rightarrow \lim_{n \rightarrow \infty} |x_n^j| \rightarrow 0 \text{ for } j = 1, 2, \dots, s$$

\Rightarrow The roots of the characteristic equation must lie within the unit circle in the complex plane.



We do not need the value of the eigenvalues.

We need to only ascertain if all the roots of the characteristic equation lie within the unit circle in the complex plane.

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simple question then actually not asking, we are not asking, we are not interested in determining the value of all the eigenvalues, we are simply interested in knowing whether all eigenvalues lie within the unit circle or not, to answer this simpler question we can develop an alternative method which is computationally simpler than finding all the roots and finding out whether they lie within unit circle or not, so that takes us to discussion on what is known as Jury's criterion where given a polynomial by using Jury's criterion we can verify whether roots of a polynomial lie within a unit circle or not, so that has bearing on discussion on stability of the finite difference time integration schemes, so what we will do is, we will take up that issue in the next lecture, and we will conclude this lecture at this stage.

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