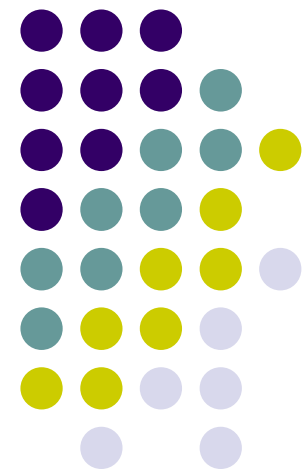


# ME751

## Advanced Computational Multibody Dynamics

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Implicit Integration Methods  
BDF Methods  
Handling Second Order EOMs  
April 06, 2010

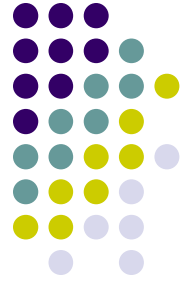


# Before we get started...



- Last Time:
  - Discussed Implicit Integration Methods, general considerations
- Today:
  - BDF Methods (one of several families of implicit numerical integration methods)
  - Dealing with 2nd order IVPs
- HW due on Th – challenging
- Exam coming up on April 29, 7:15 PM
  - Closed books (no book to open anyway)
  - Can bring one normal sheet of paper with formulas (both sides)
  - I'll provide the cheat sheet that you received a while ago
- Trip to John Deere & NADS:
  - Need head count by April 8, use forum discussion topic to indicate if you are in or not
  - Transportation and hotel will be covered
  - Leave late afternoon on May 3, return on May 4 at 10 pm or so

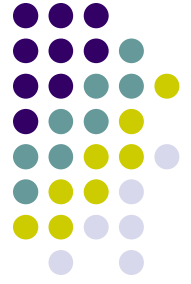
# BDF Methods



- BDF stands for Backward Differentiation Formula
- Proposed by Bill Gear in 1970
  - Super nice person
  - Back in '70s he was a professor in Comp. Science at UIUC
  - Former director of NEC Research Institute
  - Professor Emeritus, Princeton
- BDF methods are the most widely used implicit multistep methods
- BDF methods, together with HHT methods, are the two most used to integration formulas in ADAMS (the software package)



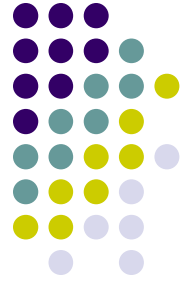
Bill Gear



# BDF Methods

## Relation to AB or AM Methods

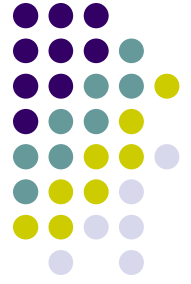
- Recall that in getting AB-M and AM-M methods, the important decision was to integrate the value of function  $f$ 
  - Integrating at  $t_n$  over  $f_{n-1}, \dots, f_{n-k}$  led to AB-M
  - Integrating at  $t_n$  over  $f_n, \dots, f_{n-k}$  led to AM-M
- The interpolation polynomial was integrated and the outcome was the family of Adams integration formulas



# BDF Methods

## Relation to AB or AM Methods

- Compared to AM and/or AB Methods, BDF formulas are obtained by making completely opposite choices
  - Rather than interpolating  $f$ , we will interpolate  $y$
  - Rather than using the interpolation polynomial to perform a time integration, the interpolation polynomial will be used in computing a time derivative
- Specifically, the points  $y_n, \dots, y_{n-k}$  are used to generate a polynomial that approximates  $y(t)$
- If one takes the time derivative of this interpolation polynomial at time  $t_n$  the value obtained should be an approximation of the time derivative of  $y(t)$ . By setting this time derivative to  $f(t_n, y_n)$  one gets a BDF method.



# BDF Methods

- The BDF methods are implicit methods
- With  $\alpha_0=1$ , they assume the form

$$\sum_{i=0}^k \alpha_i y_{n-i} = h\beta_0 f(t_n, y_n)$$

- NOTE: for  $k>6$ , the absolute stability region of the resulting BDF methods is so small that they are useless
- Example: BDF of order two

$$y_n - \frac{4}{3}y_{n-1} + \frac{1}{3}y_{n-2} = \frac{2}{3}hf(t_n, y_n)$$

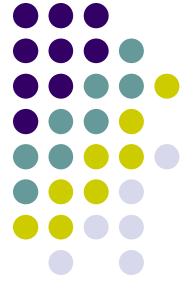
Or equivalently,

$$y_n = \frac{4}{3}y_{n-1} - \frac{1}{3}y_{n-2} + \frac{2}{3}hf(t_n, y_n)$$

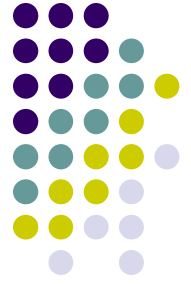
- Since BDF is a multistep method you'll need to 'prime' the method; i.e., providing the solution for a number of steps before the method is self sufficient

# Exercise

[AO, Handout]



- Find the BDF that uses  $y_n, y_{n-1}, y_{n-2}$  in approximating the solution of  $t_n$ .
  - Hint: Take the following steps
    - Build polynomial  $p(t)$  that passes through  $y_n, y_{n-1}, y_{n-2}$
    - Take time derivative of  $p(t)$  at  $t_n$  and set it to  $f(t_n, y_n)$



# BDF Methods:

$$\sum_{i=0}^k \alpha_i y_{n-i} = h\beta_0 f(t_n, y_n)$$

- Table below provides convergence order  $p$ , the number of steps  $k$  of the M method, the coefficients  $\beta_0$ , and the values of the coefficients  $\alpha_0, \alpha_1, \dots$

$p$	$k$	$\beta_0$	$\alpha_0$	$\alpha_1$	$\alpha_2$	$\alpha_3$	$\alpha_4$	$\alpha_5$	$\alpha_6$
1	1	1	1	-1					
2	2	2/3	1	-4/3	1/3				
3	3	6/11	1	-18/11	9/11	-2/11			
4	4	12/25	1	-48/25	36/25	-16/25	3/25		
5	5	60/137	1	-300/137	300/137	-200/137	75/137	-12/137	
6	6	60/147	1	-360/147	450/147	-400/147	225/147	-72/147	10/147

- Example: based on the table above, the second order BDF formula ( $k=2$ ) is

$$y_n - \frac{4}{3}y_{n-1} + \frac{1}{3}y_{n-2} = \frac{2}{3}hf(t_n, y_n) \quad \Rightarrow \quad y_n = \frac{4}{3}y_{n-1} - \frac{1}{3}y_{n-2} + \frac{2}{3}hf(t_n, y_n)$$

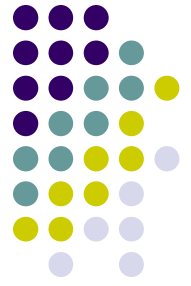


# Exercise

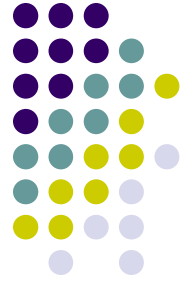


- Plot the absolute stability regions for the BDF formulas up to order 6
- Comment on the size of the region of absolute stability

# Exercise



- Prove that the BDF method with  $k=4$  is convergent with order 4
- Approach:
  - Compute the roots of the characteristic equations to prove zero-stability
  - Verify that the order conditions are satisfied up to order 4
  - Use theorem that says that  
Zero-stability + Accuracy to order  $p \Rightarrow$  Convergence of order  $p$



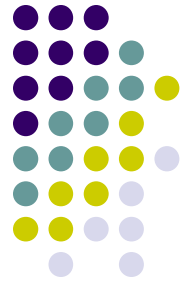
# Exercise

- Generate the convergence plot for the BDF method of order 6 for the following IVP:

$$\begin{cases} \dot{y} &= -5ty + \frac{5}{t} - \frac{1}{t^2} \\ y(1) &= 1 \end{cases}$$

- Use the analytical solution, that is,  $y(t)=1/t$ ,  $t \in [1,4]$  to generate the starting points (history) required by the integration formula
  - Note that in practice you can't count on this break for the starting points, so you will have to use RK methods or gradually increase the order of the M method used to build the required history

# BDF Method: Implementation Details (Newton Iteration)



- Recall that the BDF method is an implicit method
- Requires at each time step the solution of a nonlinear system of equations
- Approaches discussed so far for implicit multistep methods when it comes to solving the nonlinear discretization system:
  - Functional Iteration
  - PECE schemes (which can still be regarded as a flavor of Functional Iteration)
- Note that these two approaches only work for nonstiff IVPs, unless one is open to the idea of having very small step-sizes (which defeats the purpose of implicit integration...)

# BDF Method: Implementation Details (Newton Iteration)



- The approach adopted for stiff problems is to solve the discretization nonlinear system by using Newton-Raphson or some variant
- Recall the nonlinear algebraic problem that we have to solve at each time step  $t_n$ :

$$\sum_{i=0}^k \alpha_i \mathbf{y}_{n-i} = h\beta_0 \mathbf{f}(t_n, \mathbf{y}_n)$$

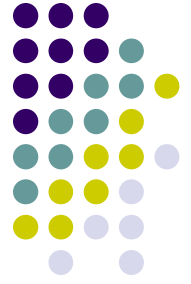
- It boils down to solving the following system of nonlinear equations:

$$\mathbf{g}(\mathbf{y}_n) \equiv \mathbf{y}_n - h\beta_0 \mathbf{f}(t_n, \mathbf{y}_n) + \mathbf{c}_n^{\mathbf{y}}(l) = \mathbf{0}$$

- Note that  $\mathbf{c}_n^{\mathbf{y}}(l)$  is a **constant** quantity that only depends on previous values of the unknown function  $\mathbf{y}$  ( $l$  stands for the order of the BDF):

$$\mathbf{c}_n^{\mathbf{y}}(l) = \sum_{i=1}^k \alpha_i \mathbf{y}_{n-i}$$

# BDF Method: Implementation Details (Newton Iteration)



- The Newton-Raphson iteration assumes the expression:

$$\begin{cases} \left( \mathbf{I} - h\beta_0 \frac{\partial \mathbf{f}}{\partial \mathbf{y}}(t_n, \mathbf{y}_n^{(\nu)}) \right) \Delta \mathbf{y}_n^{(\nu)} = -\mathbf{g}(t_n, \mathbf{y}_n^{(\nu)}) \\ \mathbf{y}_n^{(\nu+1)} = \mathbf{y}_n^{(\nu)} + \Delta \mathbf{y}_n^{(\nu)} \end{cases}$$

- The starting point is usually chosen like

$$\mathbf{y}_n^{(0)} = \mathbf{y}_{n-1}$$

- In practice, a modified Newton method is used since in the classical Newton-Raphson algorithm
  - Computing the Jacobian  $\frac{\partial \mathbf{f}}{\partial \mathbf{y}}(t_n, \mathbf{y}_n^{(\nu)})$  at each iteration is expensive
  - Computing at each iteration the **LU** factorization of the iteration matrix  $\Psi \equiv \mathbf{I} - h\beta_0 \frac{\partial \mathbf{f}}{\partial \mathbf{y}}(t_n, \mathbf{y}_n^{(\nu)})$  is expensive



# BDF Method: Implementation Details

## The Modified Newton step

- The modified-Newton assumes the form (note the (0) superscript):

$$\begin{cases} \left( \mathbf{I} - h\beta_0 \frac{\partial \mathbf{f}}{\partial \mathbf{y}}(t_n, \mathbf{y}_n^{(0)}) \right) \Delta \mathbf{y}_n^{(\nu)} = -\mathbf{g}(t_n, \mathbf{y}_n^{(\nu)}) \\ \mathbf{y}_n^{(\nu+1)} = \mathbf{y}_n^{(\nu)} + \Delta \mathbf{y}_n^{(\nu)} \end{cases}$$

- In other words, the iteration matrix is evaluated once at the beginning of the step based on the predicted value  $\mathbf{y}_n^{(0)}$
- The coefficient matrix is factored and subsequently used for all the iterations taken during that step
- You won't win the 'speed' category for your simEngine unless you implement this modified Newton approach
- This is the approach used in ADAMS

# Loose Ends

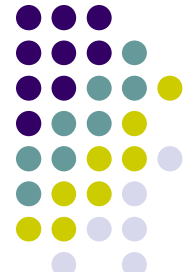


- We have not discuss about the following aspects of M methods
  - Local error estimation
  - Step size selection
  - Order selection
  - The three strategy for changing the step size
    - Fixed-coefficient strategy
    - Variable-coefficient strategy
    - Fixed leading-coefficient strategy
- These aspects discussed in Ascher-Petzold book



# [New Topic]

## Handling 2<sup>nd</sup> Order IVP



- Example:

$$\begin{cases} m\ddot{x} + c\dot{x}^3 + kx^3 = \sin(2t) \\ x(0) = x_0 \quad \rightarrow \quad \text{given to you} \\ \dot{x}(0) = v_0 \quad \rightarrow \quad \text{given to you} \end{cases}$$

- Remarks, assumptions, notation used:

- EOM for a mass-spring-damper system, see ME340 for derivation of EOM.
  - $m, c, k$  - mass, damping coefficient, spring constant, respectively
  - Spring is nonlinear, so is damping (if they were linear there was no need to Newton method to solve the ensuing problem)
  - A time periodic force,  $\sin(2t)$ , acts on the mass  $m$
- We are in the business of finding approximations for  $x$  and  $\dot{x}$ , or  $x$  and  $v$ , given the model (through the  $m, c, k$  parameters) and the force acting on the mass
    - In other words, we need to find the position and velocity of the body as a function of time  $t$
- We assume that  $c$  is large, which leads to a damped problem – you should use an implicit integrator to efficiently find the solution of this IVP

# Outcome, Dynamics Analysis

## [Nonlinear Mass-Spring-Damper]

Model Params.

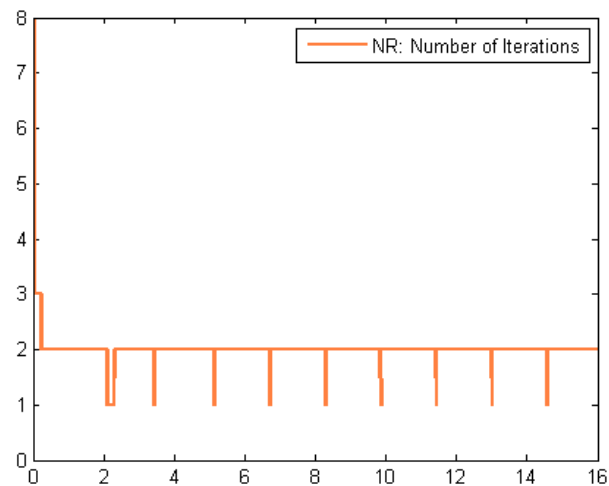
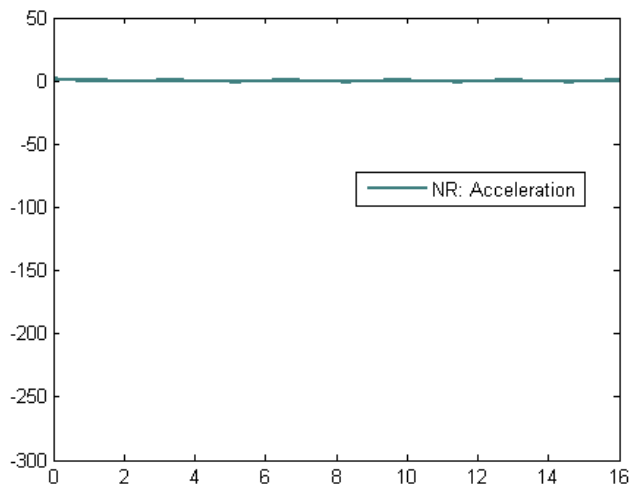
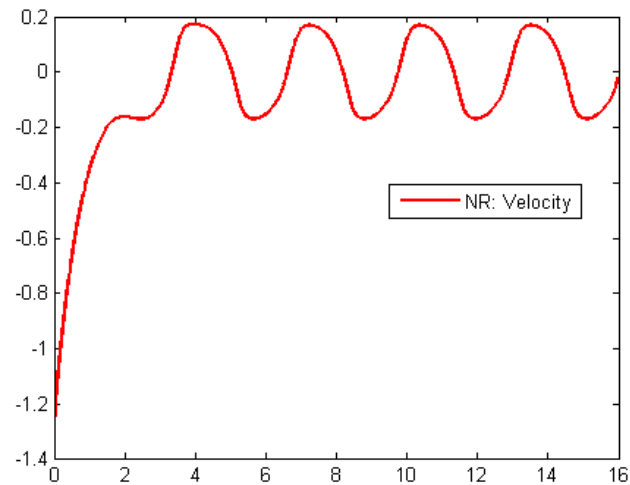
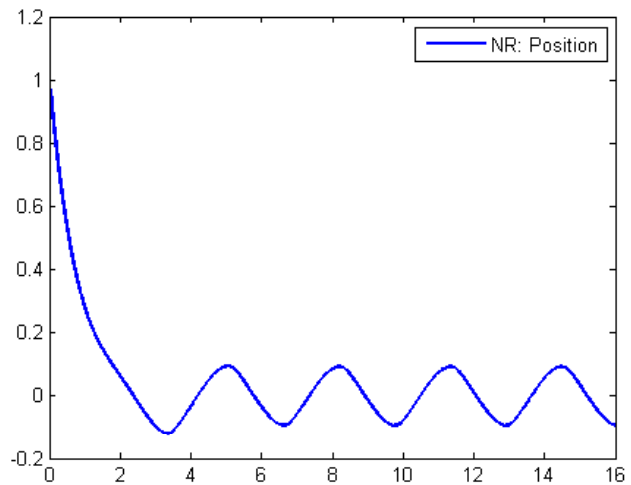
$$m = 2$$

$$c = 200$$

$$k = 400.$$

ICs:

$$x_0 = 1 \text{ and } v_0 = -1.$$



# Keeping $\dot{y}$ (instead of $f(t, y)$ ) into the Picture



- Two ways to solve this IVP, they are equivalent yet lead to different perspectives on solving the same problem:
  - Reduce 2nd order IVP to a first order IVP of dimension two and apply your favorite implicit integration formula (say BDF)
  - Keep the IVP as is, and make a simple change to your favorite implicit integration formula (we'll work with the second order BDF to introduce this approach)

- Second order BDF:

$$y_n = \frac{4}{3}y_{n-1} - \frac{1}{3}y_{n-2} + \frac{2}{3}hf(t_n, y_n)$$

- Equivalently (small but important different way of looking at the same thing),

$$y_n = \frac{4}{3}y_{n-1} - \frac{1}{3}y_{n-2} + \frac{2}{3}h\dot{y}_n$$

- Recall that we need to find the position and velocity of the mass. To this end, apply the generic BDF formula above to get through numerical integration the velocity  $v_n$  first, and then the position  $x_n$  of the mass at time step  $t_n$ :

# Expressing the Position and Velocity as Functions of Acceleration



- For velocity:

$$v_n = \frac{4}{3}v_{n-1} - \frac{1}{3}v_{n-2} + \frac{2}{3}h\dot{v}_n$$

- That is,

$$v_n = \frac{4}{3}v_{n-1} - \frac{1}{3}v_{n-2} + \frac{2}{3}ha_n$$

- Handling the position  $x_n$  now:

$$x_n = \frac{4}{3}x_{n-1} - \frac{1}{3}x_{n-2} + \frac{2}{3}h\dot{x}_n$$

- That is,

$$x_n = \frac{4}{3}x_{n-1} - \frac{1}{3}x_{n-2} + \frac{2}{3}hv_n$$

- Based on the expression of  $v_n$  above, it follows that

$$x_n = \frac{4}{3}x_{n-1} - \frac{1}{3}x_{n-2} + \frac{2}{3}h\left(\frac{4}{3}v_{n-1} - \frac{1}{3}v_{n-2} + \frac{2}{3}ha_n\right) = \frac{4}{3}x_{n-1} - \frac{1}{3}x_{n-2} + \frac{8}{9}hv_{n-1} - \frac{2}{9}hv_{n-2} + \frac{4}{9}h^2a_n$$

# Separating the Terms: Known vs. Unknown



- Important observation: take a look at the expression of the BDF integration formulas. No matter what BDF formula you use, the expression of  $x_n$  and  $v_n$  has two parts: one that depends on previous data (computed at  $t_{n-1}$ ,  $t_{n-2}$ ,  $t_{n-3}$ ,  $t_{n-4}$ , etc. - in blue below), and one that depends on data that you don't know yet, but are about to compute at  $t_n$  (in red below)

$$x_n = \frac{4}{3}x_{n-1} - \frac{1}{3}x_{n-2} + \frac{8}{9}hv_{n-1} - \frac{2}{9}hv_{n-2} + \frac{4}{9}h^2a_n$$

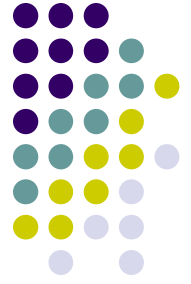
$$v_n = \frac{4}{3}v_{n-1} - \frac{1}{3}v_{n-2} + \frac{2}{3}ha_n$$

- For any BDF formula you use, say you use the one of order  $l$ , it is easy to see that  $x_n$  and  $v_n$  can be expressed as

$$x_n = C_n^x(l) + \beta_0^2 h^2 a_n$$

$$v_n = C_n^v(l) + \beta_0 h a_n$$

# Separating the Terms: The Known Terms



- Nomenclature:
  - The  $C$  in  $C_n^x(l)$  is meant to suggest that  $C_n^x(l)$  is a quantity that is a *constant*, which is evaluated based on values that were computed at previous time steps:  $t_{n-1}$ ,  $t_{n-2}$ ,  $t_{n-3}$ ,  $t_{n-4}$ , etc.
  - The  $n$  in  $C_n^x(l)$  is indicating that  $C_n^x(l)$  is evaluated at time step  $t_n$
  - The  $x$  in  $C_n^x(l)$  is indicating that this constant  $C_n^x(l)$  is the one associated with the position  $x$ . There is a constant term that is evaluated to enter the computation of  $v_n$ , like in  $C_n^v(l)$
  - The  $l$  in  $C_n^x(l)$  is indicating that  $C_n^x(l)$  is as obtained for the BDF of order  $l$ . The higher the order, the more terms  $C_n^x(l)$  and  $C_n^v(l)$  will contain.
  - HOMEWORK: We just saw how to determine  $C_n^x(2)$  and  $C_n^v(2)$ . Determine  $C_n^x(1)$  and  $C_n^v(1)$ , as well as  $C_n^x(3)$  and  $C_n^v(3)$ .
- **NOTE:** The relationships between position and acceleration, and between velocity and acceleration provided on the previous slide are **very important**. We will use it again when we solve the dynamics problem in the  $\mathbf{r} - \mathbf{p}$  formulation, and here's how:

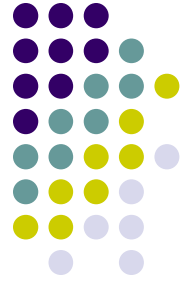
$$\mathbf{r}_n = \mathbf{C}_n^{\mathbf{r}}(l) + \beta_0^2 h^2 \ddot{\mathbf{r}}_n$$

$$\dot{\mathbf{r}}_n = \mathbf{C}_n^{\dot{\mathbf{r}}}(l) + \beta_0 h \ddot{\mathbf{r}}_n$$

$$\mathbf{p}_n = \mathbf{C}_n^{\mathbf{p}}(l) + \beta_0^2 h^2 \ddot{\mathbf{p}}_n$$

$$\dot{\mathbf{p}}_n = \mathbf{C}_n^{\dot{\mathbf{p}}}(l) + \beta_0 h \ddot{\mathbf{p}}_n$$

# The Nonlinear System



- Recall the important expressions we derived on the previous slide:

$$x_n = C_n^x(l) + \beta_0^2 h^2 a_n$$

$$v_n = C_n^v(l) + \beta_0 h a_n$$

- Recall the expression of the EOM, discretized at time  $t_n$  (discretized here means that you take the continuum ODE problem and focus on the discrete form it assumes at time  $t_n$ ):

$$m\ddot{x}_n + c\dot{x}_n^3 + kx_n^3 = \sin(2t_n)$$

- Equivalently,

$$ma_n + cv_n^3 + kx_n^3 = \sin(2t_n)$$

- Recall now that actually both  $v_n$  and  $x_n$  depend on  $a_n$ , according to our important expressions. With this in mind, define the following function  $g$  that only depends on  $a_n$ :

$$g(a_n) = ma_n + cv_n^3 + kx_n^3 - \sin(2t_n)$$

- What we want to find is the root of  $g(a_n)$ ; i.e., the solution of the equation

$$g(a_n) = 0$$

# Computing Sensitivities



$x_n$  with respect to  $a_n$

$v_n$  with respect to  $a_n$

- The key thing to keep in mind is this: when attempting to find the root of the function  $g$ , although you see  $x_n$  and  $v_n$  in its expression, recall that they both depend on  $a_n$  as indicated by the BDF formulas (our two important relations)
- Since  $x_n$  and  $v_n$  depend on  $a_n$ , in the process of searching for the root of  $g$  we will need the sensitivities of  $x_n$  and  $v_n$  with respect to  $a_n$ . Here they are:

$$\frac{\partial x_n}{\partial a_n} = \beta_0^2 h^2$$

$$\frac{\partial v_n}{\partial a_n} = \beta_0 h$$

- Being at this, recall that we'll use the same approach when carrying out Dynamics Analysis for multibody systems. The sensitivities there are computed as (see previous slide)

$$\frac{\partial \mathbf{r}_n}{\partial \mathbf{r}_n} = \beta_0^2 h^2 \mathbf{I}_{3nb \times 3nb}$$

$$\frac{\partial \dot{\mathbf{r}}_n}{\partial \dot{\mathbf{r}}_n} = \beta_0 h \mathbf{I}_{3nb \times 3nb}$$

$$\frac{\partial \mathbf{p}_n}{\partial \mathbf{p}_n} = \beta_0^2 h^2 \mathbf{I}_{4nb \times 4nb}$$

$$\frac{\partial \dot{\mathbf{p}}_n}{\partial \dot{\mathbf{p}}_n} = \beta_0 h \mathbf{I}_{4nb \times 4nb}$$



# Newton-Type Methods: Three Flavors



- We'll use variations of the same theme when it comes to finding the root of the function  $g(a_n)$ . The theme is *using Newton's method*, and the variations are as follows:
  - Straight Newton-Raphson
  - Modified Newton
  - Quasi-Newton
- Differences between the three approaches:
  - Straight Newton-Raphson updates the iteration matrix  $\Psi$  at each iteration:  $\Psi \equiv \frac{\partial g}{\partial a_n}$ . We discussed this before.
  - Modified Newton updates the iteration matrix  $\Psi$  only once in a while, typically at onset of the iterative process (we'll assume that this is the case in what follows, that is, that  $\Psi$  is evaluated at  $a_n^{(0)}$ ). We discussed this before.
  - Quasi-Newton actually works only with a rough approximation of  $\frac{\partial g}{\partial a_n}$  when searching for the root of  $g(a_n)$ . We didn't discuss this before.
- There is a subtle difference between Modified Newton and Quasi-Newton
  - In Modified Newton, you correctly and fully evaluate  $\frac{\partial g}{\partial a_n}$  for  $a_n^{(0)}$  (at the beginning of the iterative process). This *exact-when-computed* Jacobian is subsequently recycled a number of times in the iterative process
  - In Quasi-Newton, you **approximate**  $\frac{\partial g}{\partial a_n}$ . In other words, because actually computing  $\frac{\partial g}{\partial a_n}$  is expensive, you give up on some computationally expensive terms that enter its expression to obtain only an approximation of  $\frac{\partial g}{\partial a_n}$

# Newton-Type Methods: [Geometric Interpretation]



- Straight Newton-Raphson: when moving towards the root of the function, at each iteration you search in the direction given by the current tangent
- Modified Newton: when moving towards the root of the function, at each iteration you search in the direction given by the tangent evaluated at the point where you started the iterative process
- Quasi-Newton: when moving towards the root of the function, at each iteration you search in some direction that is not given by any tangent to the function. Yet, it is a direction that you computed cheaply and hopefully is not very different than the direction of the actual tangent