

Fig. 2 Ratio of mean unsteady lift coefficient to oscillatory amplitude, NACA 64A006 airfoil.

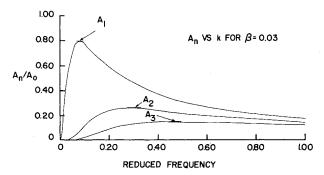


Fig. 3 Frequency dependence of mean unsteady lift coefficient for one, two, and three cycles of oscillation.

replacing Eq. (2) by a sum of exponentials, and by complicating the formalism slightly, but this will not be undertaken here.

With these values of  $\beta$  in hand, Eq. (8) was used to predict the mean unsteady amplitudes and peak amplitudes of  $C_L$ , the upper and lower shock excursions  $\delta x_{sU}$  and  $\delta x_{sL}$ , and their ratios. Note that  $\alpha_0 = 1$  here, being the ratio of oscillatory amplitude in angle of attack to the indicial step. These predictions for lift, as a function of n, are compared with the results calculated directly from oscillatory data in Fig. 2. There is good agreement for n greater than 1. Even for n = 4, the mean value of lift is still a few percent of the oscillatory amplitude. According to Eq. (8), we would have to wait at least six cycles before the discrepancy falls to a level of 1%.

Alternatively, one could use Eq. (8) to correct the results for, say, n = 4 to approximate the results for  $n \to \infty$ .

Another important aspect of this result is shown in Fig. 3, where  $A_n$  is plotted as a function of reduced frequency for n=1, 2, and 3. For the value  $\beta=0.03$  for lift, we find that  $A_1$  rises rapidly from zero to a maximum 79% at k=0.08. Similarly,  $A_2$  has its maximum at k=0.28 and  $A_3$  at k=0.47. Significantly, these frequencies are in the middle of the range of applicability of unsteady transonic finite difference codes.

#### Conclusion

Analysis of indicial data for unsteady transonic flows predicts the discrepancy between the mean oscillatory aerodynamic forces and the corresponding steady values, as well as the dependence of this discrepancy on reduced frequency and number of cycles run. A simple formula relates the time constant of the indicial response to the number of cycles of calculation needed to allow transient effects to die out.

Added note: A similar investigation by Seebass and Fung<sup>6</sup> has been brought to our attention.

#### References

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<sup>6</sup>Seebass, A. R. and Fung, K.-Y., "Unsteady Transonic Flows: Time-Linearized Calculations," *Numerical and Physical Aspects of Aerodynamic Flows*, Springer-Verlag, Berlin, 1981 (in press).

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# Digital Data Reduction of Oscillatory Signals

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### Introduction

FTEN, one is interested in the history of the amplitudes and frequencies that occur in measured signals. In case of oscillatory combustion in solid propellant rocket motors, typical propellant characteristics, such as the solid propellant response function, are derived from the amplitude growth of the pressure oscillations. Another example is the POGO-behavior of liquid propellant rocket motors, where the frequency spectrum yields important information about the propellant feedline dynamics. In order to reduce the measured data involving oscillatory signals, a Fourier analysis may be applied. However, if the signal contains oscillatory components with varying amplitudes and frequencies, Fourier analyses may become rather time-consuming. In that case, each oscillation has to be analyzed separately.

In addition, noise sometimes hampers a Fourier analysis. Usually, noise-containing signals are filtered electronically before analyzing the data, but this may cause a loss of information.

An alternative approach is to apply a purely digital recognition technique. Such a digital data reduction process has been developed recently 1 and is described here. This technique has been applied successfully to reduce data obtained during oscillatory combustion. 2 The basic approach is to select those extremes out of a series of digitized data that are considered to yield significant information about the frequency and amplitude histories.

## **Preliminary Data Processing**

In the case of an analog signal, the signal is digitized at a sample frequency at least one order of magnitude larger than the highest frequency of interest. From these digitized data only the local extremes are selected by means of the following procedure:

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Three successive datapoints,  $A_{i-1}$ ,  $A_i$ , and  $A_{i+1}$ , are compared such that if the signal levels  $E_{i-1}$ ,  $E_i$ ,  $E_{i+1}$  satisfy  $E_i - E_{i-1} > 0$  and  $E_{i+1} - E_i \le 0$ , then  $A_i$  is considered a local maximum, while if  $E_i - E_{i-1} < 0$  and  $E_{i+1} - E_i \ge 0$ ,  $A_i$  is considered a local minimum, otherwise  $A_i$  is rejected as not being an extreme.

After examining the whole series of datapoints  $A_i$  for local extremes, their characteristics are stored in a two-column array A. First column—identifier:  $I_i = 1$  in case of a local maximum,  $I_i = -1$  in case of a local minimum. Second column—local (digital) signal level  $(E_i)$ .

Note that the first and last datapoint of the original series are not included in this array. It is obvious that, owing to the character of the selection process, array A may contain series of successive similar extremes. The next step is to remove all successive similar extremes, except for the last of its kind. This decreases again the number of datapoints that are to be examined

However, it is as yet not evident whether the remaining extremes should be considered to be significant. Therefore a final selection process is applied. This process selects "significant extremes" by means of two criteria: the minimum double amplitude (MDA) and minimum relative amplitude (MRA). These criteria in fact assign a "noise level" to the signal. An amplitude which is smaller than the assigned noise level is rejected. As in some cases the noise level also depends on the mean signal level, two noise criteria are applied which have to be met simultaneously by a datapoint to be considered "significant." The values for MDA and MRA are set by the user and may be estimated from a plot of the original signal. Since these criteria are meant to be satisfied simultaneously, the MDA dominates the MRA at low mean signal levels while the opposite is the case for high mean signal levels. The combined MDA-MRA criterion covers the whole signal range.

# **Final Selection Procedure**

A flowchart of the final selection procedure, as described below, is given in Fig. 1. Since the amplitudes and mean signal levels are ultimately determined by pairs of extremes with opposite signs, and since the frequency follows from the distance of two successive maxima, the first extreme to be considered will be the first local maximum of array A. An element  $A_i$  with signal level  $E_i$  is considered to be a

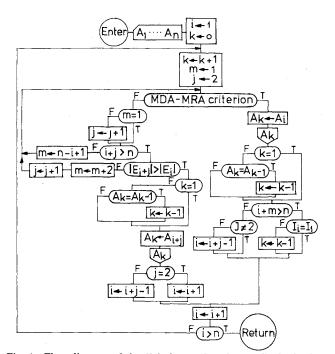


Fig. 1 Flow diagram of the digital procedure for the final selection of extremes by the MDA-MRA criterion.

meaningful extreme if it simultaneously satisfies

$$|E_i - E_{i+m}| \ge MDA$$
,  $\left| \frac{E_i - E_{i+m}}{E_i + E_{i+m}} \right| \ge MRA$ 

Initially, m is put unity, but its value may increase during the selection process such that the identifiers,  $I_i$  and  $I_{i+m}$ , always have opposite signs. If datapoint  $A_i$  satisfies the MDA-MRA criterion, it is stored as  $A_k$  in the array A. Initially, k equals unity but its value increases as more selected extremes are stored. Since at all times  $k \le i$ , storage of the elements  $A_k$  in array A will not affect the selection procedure.

In case element  $A_i$  does not satisfy the MDA-MRA criterion,  $A_i$  is to be compared with element  $A_{i+j}$ , where initially j=2. Since  $A_{i+j}$  is a similar extreme as  $A_i$ ,  $A_{i+j}$  is to be stored as  $A_k$  if  $|E_{i+j}| > |E_i|$ , while the elements  $A_i$  through  $A_{i+j-1}$  are rejected. In this case, the nature of the selection process is such that the next extreme to be subjected to the MDA-MRA criterion is element  $A_k = A_{i+j}$ .

If  $|E_i| \ge |E_{i+j}|$ , the element  $A_{i+j}$  is to be rejected and after increasing the values for m and j, the MDA-MRA criterion is applied again.

Each time that the value for i is increased by unity (i.e., a next extreme is considered), m is put unity, j is set 2, and the value for k is increased by unity. However, two conditions during the process may cause the value of k to decrease by unity. It occurs in the case that the element which is subjected to the MDA-MRA criterion has already been stored as  $A_k$  because it satisfied  $|E_{i+j}| > |E_i|$  in a previous loop.

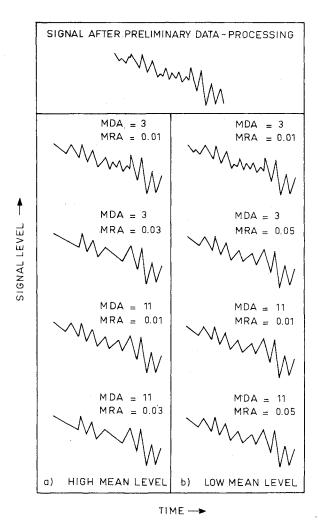


Fig. 2 Effect of the MDA and MRA values on the selection of significant extremes: a) for a high mean signal level, b) for a low mean signal level.

Decreasing k by unity also occurs to ensure that the last extreme which is to be stored is a similar extreme as the very first one. This is done because the frequency of each oscillation is determined from the distance of two successive similar extremes, as has been mentioned before. The selection process is completed either if all (n) elements of array A have been considered or if the values of m and j have increased such that array A is exhausted.

Figure 2 shows the effects that the MDA, MRA, and mean signal-level values have on the results of the final selection process. It is seen from Fig. 2a, which applies to a high mean signal-level, that a variation of the value for the MDA does not severely affect the selection process, but the value for the MRA, which dominates in this case causes significant differences. The opposite, i.e., the domination of the MDA criterion at low mean signal-levels is clearly illustrated by means of Fig. 2b.

#### Conclusion

A novel procedure has been developed to determine in an efficient, digital manner the amplitudes and frequencies of oscillatory components of arbitrary signals. Especially in those cases where varying amplitudes and frequencies are encountered, the method proves to be very useful.<sup>2</sup> The possibility to assign a noise level criterion (MDA-MRA) considerably enlarges the versatility of this procedure in comparison with other methods. Even for large amounts of data, computer times remain limited.

#### References

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# Finite Volume Method for Blade-to-Blade Flows Using a Body-Fitted Mesh

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# Introduction

THE time-dependent finite volume method provides a means of treating the problem of blade-to-blade flows in turbomachinery as an initial-value problem, since the equations for unsteady flows are always hyperbolic with respect to time in both subsonic and supersonic flow regions. On the other hand, the computation of steady flows by a time-dependent method differs from ordinary initial-value

problems in that the initial data and much of the transient solution have a negligible effect on the final or stationary solution.

The integral method first described by McDonald <sup>1</sup> and then modified by Denton <sup>2</sup> and Van Hove <sup>3</sup> is more stable than the differential methods in Refs. 3 and 4 since all fluxes are conserved. Also, the integral method overcomes the difficulties due to the complex geometries encountered in practical turbomachinery problems. The method can readily be applied to shocked flows, where the shock capturing comes through an implicit artificial viscosity. The limit on the time step imposed by the stability requirement is the main disadvantage of time-marching methods.

The objective of this paper is to describe an efficient and accurate approach to the time-dependent finite-volume method applied to blade-to-blade flows in two dimensions. The approach developed consists of solving the Euler equations in conservation law form on a curvilinear body-fitted mesh.

The flow is assumed to be homenergic, so that the energy equation can be omitted. However, homenergic flow is only physical in the asymptotic limit of steady state. The time-marching computation will not represent a true unsteady phenomena, and this assumption is only used to reduce the computing time. This is made possible by the fact that a sound wave in a homenergic flow travels with a lower speed than in an isentropic flow. Furthermore, this model requires one less variable.

# **Body-Fitted Curvilinear Meshes**

In the application of the finite volume method, one generally assumes, for convenience, that the mesh is aligned with the flowfield, and this, to a large extent, will determine the accuracy of the solution. Denton's grid is the most widely used due to its simplicity. Generally, the grids used by previous authors are not very well aligned, and to increase the accuracy one must resort to the use of a finer grid, especially in the critical regions of the flowfield. These are regions where the properties vary rapidly such as the leading and trailing edges, and where the flow alignment with the grid is bad. Such grid refinement will result in an increase in computer time, since a sound wave cannot travel more than one mesh width in one time increment, which is the required condition for stability. This increase of computer time will be very pronounced in the case of a uniform time step, while in the case of a nonuniform time step, the increase will be directly proportional to the ratio between the number of nodes in the fine regions to the total number of nodes. Figure 1 shows a refined Denton grid.

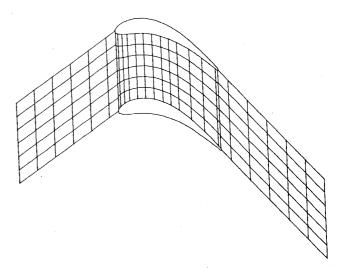


Fig. 1 Denton's grid (with concentration of nodes on the leading and trailing edges).

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