# Weighted essentially non-oscillatory schemes

Matthew Emmett

January 14, 2010

## 1 Introduction

We follow C.W. Shu in "Essentially Non-oscillatory and Weighted Essentially Non-oscillatory Schemes for Hyperbolic Conservation Laws" (NASA/CR-97-206253, ICASE report no. 97-65).

Weighted esstentially non-oscillatory (WENO) techniques have many applications. We will focus our attention on one-dimensional hyperbolic conservation law of the form

$$q_t + \big(f(q)\big)_x = 0. \tag{1.1}$$

Finite-volume schemes do not solve (1.1) directly. They solve its integrated version instead. Integrating (1.1) over the interval $[a, b]$ we obtain

$$\frac{d}{dt}\overline{q}(t) + \frac{1}{b-a}\Big(f\big(q(b,t)\big) - f\big(q(a,t)\big)\Big) = 0$$

where

$$\overline{q}(t) \equiv \frac{1}{b-a}\int_a^b q(\xi, t)\, d\xi$$

is the average value of $q$ over $[a, b]$. This leads us to one of the central problems in implementing a numerical scheme to solve (1.1): obtaining the values of $q$ at the boundaries $a$ and $b$ based on the average $\overline{q}$ of $q$. This is the *reconsturction* problem.

## 2 Grid

We consider a grid over the interval $[a, b]$ with $N$ cells. We denote the $N + 1$ cell boundaries by

$$x_{i-1/2} \quad \text{for} \quad i = 1, \ldots, N + 1 \tag{2.1}$$

so that

$$a = x_{1/2} < x_{3/2} < \cdots < x_{N-1/2} < x_{N+1/2} = b. \tag{2.2}$$

Subsequently, we denote the $N$ cells by

$$C_i = [x_{i-1/2}, x_{i+1/2}] \quad \text{for} \quad i = 1, \ldots, N; \tag{2.3}$$

the $N$ cell centres by

$$x_i = \frac{x_{i-1/2} + x_{i+1/2}}{2} \quad \text{for} \quad i = 1, \ldots, N; \tag{2.4}$$

the $N$ cell sizes by

$$\Delta x_i = x_{i+1/2} - x_{i-1/2} \quad \text{for} \quad i = 1, \ldots, N; \tag{2.5}$$

and the maximum cell size by

$$\Delta x = \max_{i=1,\ldots,N} \Delta x_i. \tag{2.6}$$

We denote the contiguous stencil around the cell $C_i$, containing $k$ cells shifted to the left by $r$ cells, by

$$S_i^{r,k} = C_{i-r} \cup \cdots \cup C_{i-r+k-1}. \tag{2.7}$$

Note that $S_i^{r,k}$ spans $k$ cells and contains $k + 1$ cell boundaries.

## 3 One dimensional reconstruction for smooth functions

Given the cell averages $\overline{f}_j$ of a function $f$ where

$$\overline{f}_j = \frac{1}{\Delta x_j} \int_{x_{j-1/2}}^{x_{j+1/2}} f(\xi)\, d\xi \tag{3.1}$$

we wish to find approximations to the function $f$ at various points within each cell. In particular, we might be interested in approximating the function at the left cell boundary $x_{i-1/2}$, the right cell boundary $x_{i+1/2}$, or at any point $\xi$ within the cell $C_i$. If the approximations are computed using $k$ cell averages, they should be $k$-order accruate. The remainder of this section will be devoted to finding these approximations and showing that they are $k$-order accuarate. As it turns out, we will show that there are constants $c_j$ (hereafter called *reconstruction coefficients*) such that the reconstructed values are given by

$$f(\xi) \approx \sum_{j=0}^{k-1} c_j\, \overline{f}_{i-r+j}.$$

That is, given a stencil $S_i^{r,k}$ that spans the $k$ cells $C_{i-r}, \ldots, C_{i-r+k-1}$, the reconstructed value of the original function at some point $\xi$ in $C_i$ can be obtained using the cell averages $\overline{f}_j$ over the cells $C_j$ in the stencil $S_i^{r,k}$. In general, the reconstruction coefficients $c_j$ depend on the reconstruction point $\xi$, order $k$, left shift $r$, and cell $C_i$, but *not* on the function $f$.

In order to obtain the reconstruction coefficients $c_j$ and prove accuracy, we will find polynomials $p_i^r$ of degree at most $k-1$ such that each $p_i^r$ is a $k$-order accurate approximation to $f$ inside $C_i$. That is, given the cell averages $\overline{f}_j$, we will find polynomials $p_i^r$ such that

$$p_i^r(x) = v(x) + O(\Delta x^k) \quad \text{for} \quad x \in C_i.$$

In order to find these polynomials, we consider the function

$$V(x) = \int_a^x f(\xi)\, d\xi. \tag{3.2}$$

Using the cell averages $\overline{f}_j$ we can compute $V$ at the cell boundaries $x_{i+1/2}$ through

$$\begin{aligned} V(x_{i+1/2}) &= \int_a^{x_{i+1/2}} f(\xi)\, d\xi \\ &= \sum_{j=1}^{i} \int_{x_{j-1/2}}^{x_{j+1/2}} f(\xi)\, d\xi \\ &= \sum_{j=1}^{i} \overline{f}_j \Delta x_j. \end{aligned} \tag{3.3}$$

Focusing on a particular cell $C_i$ and stencil $S_i^{r,k}$, the unique polynomial $P_i^r$ of order $k$ which interpolates $V$ at the $k+1$ points

$$x_{i-r-1/2}, \ldots, x_{i-r+k-1/2}$$

is given by

$$P_i^r(x) = \sum_{l=0}^{k} \left( V(x_{i-r+l-1/2}) \prod_{m=0, m\neq l}^{k} \frac{(x - x_{i-r+m-1/2})}{(x_{i-r+l-1/2} - x_{i-r+m-1/2})} \right). \tag{3.4}$$

This is the interpolating polynomial of $V$ in Lagrange form. It can be shown (see Appendix A) that

$$P_i^r(x) = V(x) + O(\Delta x^{k+1}) \quad \text{for} \quad x \in S_i^{r,k}.$$

Therefore, the derivative $p_i^r$ of $P_i^r$ satisfies

$$p_i^r(x) = \frac{d}{dx} P_i^r(x) = f(x) + O(\Delta x^k) \quad \text{for} \quad x \in S_i^{r,k}$$

and $p_i^r$ is of order $k-1$.

Furthermore, the cell averages of $p_i^r$ over the cells $C_j$ that comprise the stencil $S_i^{r,k}$ satisfy

$$\begin{aligned}
\frac{1}{\Delta x_j} \int_{x_{j-1/2}}^{x_{j+1/2}} p_i^r(\xi)\, d\xi &= \frac{1}{\Delta x_j} \int_{x_{j-1/2}}^{x_{j+1/2}} P_i'(\xi)\, d\xi \\
&= \frac{1}{\Delta x_j} \Big( P_i^r(x_{j+1/2}) - P_i^r(x_{j-1/2}) \Big) \\
&= \frac{1}{\Delta x_j} \Big( V(x_{j+1/2}) - V(x_{j-1/2}) \Big) \\
&= \frac{1}{\Delta x_j} \left( \int_a^{x_{j+1/2}} f(\xi)\, d\xi - \int_a^{x_{j-1/2}} f(\xi)\, d\xi \right) \\
&= \frac{1}{\Delta x_j} \left( \int_{x_{j-1/2}}^{x_{j+1/2}} f(\xi)\, d\xi \right) \\
&= \overline{f}_j \quad \text{for} \quad j = i-r, \ldots, i-r+k-1.
\end{aligned}$$

That is, the cell averages of the approximating polynomials $p_i^r$ match the cell averages the original function in each of the cells $C_j$ which comprise the stencil $S_i^{r,k}$.

So far we have constructed polynomials $p_i^r$ that approximate the original function $f$ on the stencils $S_i^{r,k}$ to $k$-order using only the cell averages $\overline{f}_j$ for $j = i-r, \ldots, i-r+k-1$.

Now we consider the practical problem of finding the constants $c_j$. Subtracting $V(x_{i-r-1/2})$ from $P_i^r(x)$ and using

$$\sum_{l=0}^{k} \prod_{m=0, m\neq l}^{k} \frac{(x - x_{i-r+m-1/2})}{(x_{i-r+l-1/2} - x_{i-r+m-1/2})} = 1 \quad \text{and} \quad V(x_{i-r+l-1/2}) - V(x_{i-r-1/2}) \equiv 0 \text{ for } l = 0$$

we obtain

$$P_i^r(x) - V(x_{i-r-1/2}) = \sum_{l=1}^{k} \left( \big(V(x_{i-r+l-1/2}) - V(x_{i-r-1/2})\big) \prod_{m=0, m\neq l}^{k} \frac{(x - x_{i-r+m-1/2})}{(x_{i-r+l-1/2} - x_{i-r+m-1/2})} \right).$$

Taking the derivative of the above, we obtain

$$\frac{d}{dx} P_i^r(x) = \frac{d}{dx} \left[ \sum_{l=1}^{k} \left( \big(V(x_{i-r+l-1/2}) - V(x_{i-r-1/2})\big) \prod_{m=0, m\neq l}^{k} \frac{(x - x_{i-r+m-1/2})}{(x_{i-r+l-1/2} - x_{i-r+m-1/2})} \right) \right]$$

and hence

$$p_i^r(x) = \sum_{l=1}^{k} \left( \big(V(x_{i-r+l-1/2}) - V(x_{i-r-1/2})\big) \frac{\sum_{m=0, m\neq l}^{k} \prod_{n=0, n\neq l,m}^{k} (x - x_{i-r+n-1/2})}{\prod_{m=0, m\neq l}^{k} (x_{i-r+l-1/2} - x_{i-r+m-1/2})} \right). \tag{3.5}$$

Employing (3.3), we obtain

$$p_i^r(x) = \sum_{l=1}^{k} \left( \left( \sum_{j=0}^{l-1} \overline{f}_{i-r+j} \Delta x_{i-r+j} \right) \frac{\sum_{m=0, m\neq l}^{k} \prod_{n=0, n\neq l,m}^{k} (x - x_{i-r+n-1/2})}{\prod_{m=0, m\neq l}^{k} (x_{i-r+l-1/2} - x_{i-r+m-1/2})} \right). \tag{3.6}$$

Rearranging, we obtain

$$p_i^r(x_{i+1/2}) = \sum_{j=0}^{k-1} \sum_{l=j+1}^{k} \frac{\sum_{m=0,m\neq l}^{k} \prod_{n=0,n\neq l,m}^{k} (x - x_{i-r+n-1/2})}{\prod_{m=0,m\neq l}^{k} (x_{i-r+l-1/2} - x_{i-r+m-1/2})} \ \Delta x_{i-r+j} \overline{v}_{i-r+j}.$$

Therefore, the reconstruction coefficients $c_j$ used to reconstruct the function $f$ at the point $\xi$ are given by

$$c_j = \sum_{l=j+1}^{k} \frac{\sum_{m=0,m\neq l}^{k} \prod_{n=0,n\neq l,m}^{k} (\xi - x_{i-r+n-1/2})}{\prod_{m=0,m\neq l}^{k} (x_{i-r+l-1/2} - x_{i-r+m-1/2})} \ \Delta x_{i-r+j}. \tag{3.7}$$

Note that the the reconstruction coefficients $c_j$ depend on $\xi$, $i$, $r$, and $k$.

## 3.1 Further derivatives

In order to approximate the first derivative of the original function $f$ we consider the first derivative of $p_i^r(x)$. We obtain

$$\begin{aligned} \frac{d}{dx} p_i^r(x) &= \frac{d}{dx} \left[ \sum_{l=1}^{k} \left( \left( V(x_{i-r+l-1/2}) - V(x_{i-r-1/2}) \right) \ \frac{\sum_{m=0,m\neq l}^{k} \prod_{n=0,n\neq l,m}^{k} (x - x_{i-r+n-1/2})}{\prod_{m=0,m\neq l}^{k} (x_{i-r+l-1/2} - x_{i-r+m-1/2})} \right) \right] \\ &= \sum_{l=1}^{k} \left( \left( V(x_{i-r+l-1/2}) - V(x_{i-r-1/2}) \right) \ \frac{\sum_{m=0,m\neq l}^{k} \sum_{n=0,n\neq l,m}^{k} \prod_{p=0,p\neq l,m,n} (x - x_{i-r+p-1/2})}{\prod_{m=0,m\neq l}^{k} (x_{i-r+l-1/2} - x_{i-r+m-1/2})} \right). \end{aligned}$$

Employing (3.3), we obtain

$$\frac{d}{dx} p_i^r(x) = \sum_{l=1}^{k} \left( \left( \sum_{j=0}^{l-1} \overline{v}_{i-r+j} \Delta x_{i-r+j} \right) \frac{\sum_{m=0,m\neq l}^{k} \sum_{n=0,n\neq l,m}^{k} \prod_{p=0,p\neq l,m,n} (x - x_{i-r+p-1/2})}{\prod_{m=0,m\neq l}^{k} (x_{i-r+l-1/2} - x_{i-r+m-1/2})} \right).$$

Rearranging, we obtain

$$\frac{d}{dx} p_i^r(x) = \sum_{j=0}^{k-1} \sum_{l=j+1}^{k} \frac{\sum_{m=0,m\neq l}^{k} \sum_{n=0,n\neq l,m}^{k} \prod_{p=0,p\neq l,m,n} (x - x_{i-r+p-1/2})}{\prod_{m=0,m\neq l}^{k} (x_{i-r+l-1/2} - x_{i-r+m-1/2})} \ \Delta x_{i-r+j} \overline{v}_{i-r+j}.$$

Therefore, the reconstruction coefficients for the first derivative are

$$c_j = \sum_{l=j+1}^{k} \frac{\sum_{m=0,m\neq l}^{k} \sum_{n=0,n\neq l,m}^{k} \prod_{p=0,p\neq l,m,n} (\xi - x_{i-r+p-1/2})}{\prod_{m=0,m\neq l}^{k} (x_{i-r+l-1/2} - x_{i-r+m-1/2})} \ \Delta x_{i-r+j}$$

## 3.2 Summary

In summary, given a stencil $S_i^{r,k}$ and the cell averages $\overline{f}_j$ of a function $f$, we can reconstruct $f$ at any point $\xi$ in the cell $C_i$ according to

$$f(\xi) \approx \sum_{j=0}^{k-1} c_j \ \overline{f}_{i-r+j} \tag{3.8}$$

where

$$c_j = \sum_{l=j+1}^{k} \frac{\sum_{m=0,m\neq l}^{k} \prod_{n=0,n\neq l,m}^{k} (\xi - x_{i-r+n-1/2})}{\prod_{m=0,m\neq l}^{k} (x_{i-r+l-1/2} - x_{i-r+m-1/2})} \ \Delta x_{i-r+j}. \tag{3.9}$$

Furthermore, the approximation is accurate to order $k$ so that

$$\sum_{j=0}^{k-1} c_j \, \overline{f}_{i-r+j} = f(\xi) + O(\Delta x^k)$$

where

$$\Delta x = \max_{j=i-r,\ldots,i-r+k-1} \Delta x_j.$$

The permissable values of left shift parameter $r$ in (3.8) are $-1, \ldots, k-1$ so that the results of Appendix A hold.

# 4 One dimensional reconstruction for piece-wise smooth functions

The solutions of hyperbolic conservation laws may contain discontinuities, and therefore we are interested in reconstructing piecewise smooth functions. A piecewise smooth function $f$ is smooth except at finitely many isolated points. At these points, $f$ and its derivatives (at least up to the order of the scheme) are assumed to have finite left and right limits.

For such piecewise smooth functions, the order of accuracy herein referred to is formal. That is, it is defined as the accuracy determined by the local error in the smooth regions of the function.

The basic idea of WENO is to use a convex combination of several stencils to form the reconstruction of $f$, and, if a stencil contains a discontinuity, its weight should be close to zero. In smooth regions, using several stencils will also serve to increase the order of accuracy.

Consider the $k$ stencils

$$S_i^{r,k} \quad \text{for} \quad r = 0, \ldots, k-1$$

that can be used to reconstruct the value of $f$ at some point $\xi$ in the cell $C_i$. These stencils span $2k-1$ cells. We denote the $k$ different reconstructions by

$$f(\xi) \approx f^r = \sum_{j=0}^{k-1} c_j^r \bar{v}_{i-r+j} \quad \text{for} \quad r = 0, \ldots, k-1 \tag{4.1}$$

where we have added the superscript $r$ to the function $f$ and the reconstruction coefficients $c_j$ to make their dependance on the left shift $r$ explicit.

A WENO reconstruction takes a convex combination of all $f^r$ defined in (4.1) as a new approximation according to

$$f(\xi) \approx \sum_{r=0}^{k-1} \omega_i^r f^r \tag{4.2}$$

where we require

$$\omega_i^r \geq 0 \quad \text{and} \quad \sum_{r=0}^{k-1} \omega_i^r = 1. \tag{4.3}$$

In smooth regions where all $k$ stencils that can be used to reconstruct $f(\xi)$ in (4.1) do not contain discontinuities, we could reconstruct $f(\xi)$ to order $2k-1$ using the stencil $S_i^{k-1,2k-1}$ to obtain

$$f(\xi) = \sum_{j=0}^{2k-2} c_j^* \, \bar{f}_{i-(k-1)+j} \tag{4.4}$$

where we have added the superscript $*$ to the reconstruction coefficients $c_j$ to highlight that they are optimal (ie, higher order). Combining (4.1), (4.2), and (4.4), we obtain

$$\sum_{j=0}^{2k-2} c_j^* \, \bar{f}_{i-(k-1)+j} = \sum_{r=0}^{k-1} \omega_i^r \left( \sum_{l=0}^{k-1} c_l^r \, \bar{f}_{i-r+l} \right). \tag{4.5}$$

Rearranging, we obtain

$$\sum_{j=0}^{2k-2} c_j^* \, \bar{f}_{i-(k-1)+j} = \sum_{j=0}^{2k-2} \left( \sum_{l=\max(0,j-k+1)}^{\min(k-1,j)} \omega_i^{k-(j+1)+l} c_l^{k-(j+1)+l} \right) \bar{f}_{i-(k-1)+j}.$$

Therefore, we have $2k-1$ equations

$$\sum_{l=\max(0,j-k+1)}^{\min(k-1,j)} \omega_i^{k-(j+1)+l} c_l^{k-(j+1)+l} = c_j^* \quad \text{for} \quad j=0,\dots,2k-2 \tag{4.6}$$

at each $i$ (and $\xi$) for the weights $\omega_i^r$. For unstructured grids the systems (4.6) are over-determined, and therefore we must use some kind of optimisation algorithm in order to find the weights $\omega_i^r$. For structured grids the systems (4.6) are no longer over-determined, and the weights $\omega_i^r$ can be found explicity (and are independent of $i$).

The weights $\omega_i^r$ defined by (4.5) and determined by (4.6) are called *optimal weights* since they can be used to reconstruct a function to order $2k-1$ in regions where the function is smooth. We will henceforth denote the optimal weights by $\varpi_i^r$.

We now consider the practical problem of choosing the weights $\omega_i^r$. If we choose the weights $\omega_i^r$ sufficiently close to the optimal weights $\varpi_i^r$ in regions where the function is smooth, then we can achieve $2k-1$ order accuracy. In order to determine how close to the optimal weights $\varpi_i^r$ the weights $\omega_i^r$ must be choosen we consider the reconstruction

$$f(\xi) \approx \sum_{r=0}^{k-1} \omega_i^r f^r = \sum_{r=0}^{k-1} \varpi_i^r f^r + \sum_{r=0}^{k-1} \big(\omega_i^r - \varpi_i^r\big) f^r. \tag{4.7}$$

If we choose

$$\omega_i^r = \varpi_i^r + O(\Delta x^{k-1}) \tag{4.8}$$

then each term in the last summation of (4.8) becomes $O(\Delta x^{2k-1})$ and therefore $2k-1$ order accuracy is preserved by the reconstruction.

If we define

$$\omega_i^r = \frac{\alpha_i^r}{\alpha_i^0 + \cdots + \alpha_i^{k-1}} \tag{4.9}$$

where

$$\alpha_i^r = \frac{\varpi_i^r}{(\epsilon + \sigma_i^r)^p} \quad \text{for} \quad r = 0,\dots,k-1; \tag{4.10}$$

and $\epsilon$ is a positive real number used to avoid dividing by zero (usually $\epsilon = 10^{-6}$), $p$ is some power (usually 2), and $\sigma_i^r$ is a measure of the smoothness of the function $v$ in the stencil $S_i^{r,k}$; with the smoothnesses $\sigma_i^r$ chosen appropriately, then (4.8) is satisfied.

Typically, the smoothness measurement presented by Jiang and Shu is used. They define the smoothness according to

$$\sigma_i^r = \sum_{l=1}^{k-1} \int_{x_{j-1/2}}^{x_{j+1/2}} (\Delta x_j)^{2l-1} \left( \frac{d^l}{dx^l} p_i^r(x) \right)^2 \, dx \tag{4.11}$$

which is the sum of the $L^2$ norms of the derivatives of the approximating polynomial.

### 4.1 One-sided (up/down wind) reconstructions

In some situations we may need to impose that some cells be excluded from the reconstruction process. For example, at the front of a dam-break flow with a positive front velocity there is a wet-dry interface and the dry cells to the right of the front should be avoided.

A *left-biased* WENO reconstruction is one in which the weights

$$\omega_i^r = 0 \quad \text{for} \quad r < s$$

where $s > 0$ is some parameter that controls how many cells are excluded from the reconstruction (4.2). Intuitively, $s$ is also the number of cells to exlude from the right.

A *right-biased* WENO reconstruction is one in which the weights

$$\omega_i^r = 0 \quad \text{for} \quad r > k - |s| - 1$$

where $s < 0$ is some parameter that controls how many cells are excluded from the reconstruction (4.2). Intuitively, $|s|$ is also the number of cell to exclude from the left.

That is, if $s > 0$ the WENO reconstruction will be left-biased and reconstructions with $r < s$ will be ignored; if $s < 0$ the WENO reconstruction will be right-biased and reconstructions with $r > k - |s| - 1$ will be ignored. Once again, we need to determine optimal weights for both left- and right-biased reconstructions.

For left-biased reconstructions ($s > 0$), we reconstruct $f(\xi)$ to order $2k - s - 1$ using the stencil $S_i^{k-1,\, 2k-s-1}$ to obtain the optimal reconstruction coefficients $c_j^*$ (similar to (4.4)). Therefore, similar to (4.6), we have $2k - s - 1$ equations

$$\sum_{l=\max(0,j-k+s+1)}^{\min(k-1,j)} \omega_i^{k-(j+1)+l} c_l^{k-(j+1)+l} = c_j^* \quad \text{for} \quad j = 0, \ldots, 2k - s - 2. \tag{4.12}$$

For right-biased reconstructions ($s < 0$), we reconstruct $f(\xi)$ to order $2k - |s| - 1$ using the stencil $S_i^{k-|s|-1,\, 2k-|s|-1}$ to obtain the optimal reconstruction coefficients $c_j^*$ (similar to (4.4)). Therefore, similar to (4.6), we have $2k - |s| - 1$ equations

$$\sum_{l=\max(0,j-k+|s|+1)}^{\min(k-1,j)} \omega_i^{k-(j+1)+l} c_l^{k+s-(j+1)+l} = c_j^* \quad \text{for} \quad j = 0, \ldots, 2k - |s| - 2. \tag{4.13}$$

# A Error of Lagrange interpolating polynomials

Let $f(x) \in C^n([a,b])$, and $p(x)$ be the interpolating polynomial of degree $n-1$ such that

$$p(x_i) = f(x_i) \quad \text{for} \quad i = 1, \dots, n \tag{A.1}$$

where

$$a = x_1 < x_2 < \cdots < x_{n-1} < x_n = b. \tag{A.2}$$

Then

$$p(x) = f(x) + O(\Delta x^n) \quad \text{for} \quad x \in [a,b] \tag{A.3}$$

where

$$\Delta x = \max_{i=2,\dots,n} x_i - x_{i-1}. \tag{A.4}$$

**Proof.** Let $x \in [a,b]$. If $x = x_i$ for some $i = 1, \dots, n$ then $f(x) - p(x) = 0$ since $p(x)$ is the interpolating polynomial. Otherwise, let

$$\Phi(x) = \frac{f(x) - p(x)}{\prod_{i=1}^{n}(x - x_i)} \tag{A.5}$$

and

$$g(x,\xi) = f(\xi) - p(\xi) - \Phi(x) \prod_{i=1}^{n} (\xi - x_i). \tag{A.6}$$

Then $g(x,\xi)$ is $n$ times differentiable with respect to $\xi$, $g(x, x_i) = 0$ for $i = 1, \dots, n$, and $g(x,x) = 0$. Applying Rolle's theorem successively across all interpolation points $x_i$ and $x$ we obtain

$$\left. \frac{\partial^n}{\partial \xi^n} g(x,\xi) \right|_{\xi = \xi^*} = 0 \tag{A.7}$$

for some $\xi^* \in (a,b)$. Futhermore

$$\frac{\partial^n}{\partial \xi^n} g(x,\xi) = f^n(\xi) - n!\, \Phi(x) \tag{A.8}$$

so that, combininig (A.7) and (A.8), we obtain

$$\Phi(x) = \frac{f^n(\xi^*)}{n!} \tag{A.9}$$

and therefore

$$f(x) - p(x) = \frac{f^n(\xi^*)}{n!} \prod_{i=1}^{n} (x - x_i). \tag{A.10}$$

Finally, we conclude that

$$p(x) = f(x) + O(\Delta x^n). \tag{A.11}$$

That is, if $p(x)$ interpolates $f(x)$ at $n$ points, then it is accurate to $O(\Delta x^n)$ where $\Delta x$ is the maximum space between the interpolating points.