

On the Newton Multivariate Polynomial Interpolation with Applications

Dimitris N. Varsamis and Nicholas P. Karampetakis

Abstract— The main purpose of this work is to provide an optimized version of the Newton divided-difference algorithm presented by [11] for the polynomial interpolation problem. This optimized algorithm is used for the computation of the determinant of a two-variable polynomial matrix.

I. INTRODUCTION

INTERPOLATION, is the problem of approximating a function f , with another function g more usable, when its values at distinct points are known. When the function g is a polynomial we call the method *polynomial interpolation*. Polynomial interpolation of single variable functions is a rather old method in applied mathematics [6]. However, polynomial interpolation in several variables is a relatively new topic that has received not deep but constant attention from one part of the mathematical community and is today a basic subject of Approximation Theory and Numerical Analysis with applications to many mathematical problems.

The problem of the multivariate interpolation has been the concern of many scientists [2], [5], [11], [12]. Some of the most known multivariate interpolation methods are: a) the use of a multivariate Vandermode matrix and its LU factorization [12], b) the Lagrange interpolation [14], [15] c) the Hermite-Birkhoff interpolation [4] and d) the Newton-form interpolation [11], [14].

Although the one-variable interpolation has always solution for given *distinct* points, the multivariate interpolation problem through arbitrary given points may or may not have a solution when the number of unknown polynomial coefficients agree with the number of points. An interpolation problem is defined to be *poised* if it has a unique solution. Unlike the one-variable interpolation problem, the Hermite, Lagrange and Newton-form multivariate interpolation problem is not always poised. However, by selecting a specific location of the interpolation points, we can always have a unique solution.

In the special case of the *polynomial interpolation*

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problem, the speed of interpolation algorithms can be increased by using Discrete Fourier Transforms (DFT) techniques or better Fast Fourier Transforms (FFT) [10]. DFT-based algorithms, are used in many applications i.e. the calculation of the determinantal polynomial [13], the computation of the transfer function of generalized n-dimensional systems [1], the solutions of polynomial matrix Diophantine equations [7], and the computation of the generalized inverse of multivariable polynomial matrices [8], [17]. Recently, [9] proposed a Lagrange interpolation method for the computation of the inverse (and thus of the determinant) of a two-variable polynomial matrix by extending the results presented by [13] and [16].

In this work, we provide a better insight on the Newton-form *polynomial interpolation* method. More specifically, we present in section 2, the Newton divided-difference algorithm presented by [11] for an arbitrary function $f(x, y)$ in a slightly different way. Then, in section 3, we present an alternative algorithm for the special case where $f(x, y)$ is a polynomial with known upper bounds for the degrees of each variable. This new algorithm is using a subset of the interpolation points that Neidinger's algorithm is using and therefore it is a better one as concerns the complexity. Finally, in the last section we present an application of this new algorithm on the computation of the determinant of a two-variable polynomial matrix.

II. THE ALGORITHM FOR MULTIVARIABLE INTERPOLATING POLYNOMIAL IN NEWTON FORM

In this section, we present the Newton divided-difference algorithm presented by [11] for two-variable interpolation polynomials in a slightly different way. The main difference with [11] is the procedure that we use for computing the divided-differences.

It is known [14, Theorem 5.2.1, pp.178], that given any positive integer n and a set of points $S_\Delta^n = \{(x_i, y_j) \mid i, j \geq 0, i + j \leq n\}$ where x_i are distinct and y_j are distinct, there is a *unique* polynomial of the form

$$P_n(x, y) = \sum_{i=0}^n \sum_{j=0}^{n-i} a_{i,j} x^i y^j \quad (2.1)$$

that takes the same values as a given function $f(x, y)$ on

the set S_{Δ}^n .

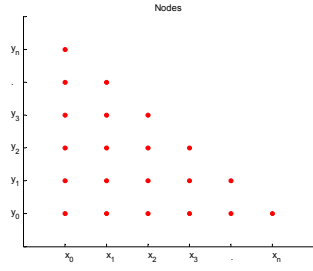


Fig. 1. An example of the set S_{Δ}^n .

In the following algorithm, we show how to construct this interpolating polynomial by using an alternative Newton divided difference formula for a set of points S_{Δ}^n .

Algorithm 1. Construction of a Newton interpolating two-variable polynomial $P_n(x, y)$ (defined in (2.1)) for a function $f(x, y)$.

Step 1: $k=0$. Based on the values of $f(x, y)$ at the set of points S_{Δ}^n we can construct the zero order table of initial values

$$\begin{array}{c|cccc} & x_0 & x_1 & x_2 & \cdots & x_n \\ \hline y_0 & P_{0,0}^{(0)} & P_{1,0}^{(0)} & P_{2,0}^{(0)} & \cdots & P_{n,0}^{(0)} \\ y_1 & P_{0,1}^{(0)} & P_{1,1}^{(0)} & \cdots & & P_{n-1,1}^{(0)} \\ y_2 & P_{0,2}^{(0)} & \vdots & \ddots & & \\ \vdots & \vdots & P_{1,n-1}^{(0)} & & & \\ y_n & P_{0,n}^{(0)} & & & & \end{array} \quad (2.2)$$

where $P_{i,j}^{(0)} = f(x_i, y_j)$.

Step 2: For $k=1(1)n$, compute the k^{th} -order table of divided differences given by the recursive form

$$P_{i,j}^{(k)} := \begin{cases} \frac{P_{i,j}^{(k-1)} - P_{i-1,j}^{(k-1)}}{x_i - x_{i-k}} & \text{if } (j \leq k-1 \wedge i > k-1) \\ \frac{P_{i,j}^{(k-1)} - P_{i,j-1}^{(k-1)}}{y_j - y_{j-k}} & \text{if } (i \leq k-1 \wedge j > k-1) \\ \frac{P_{i,j}^{(k-1)} + P_{i-1,j+1}^{(k-1)} - P_{i,j-1}^{(k-1)} - P_{i-1,j}^{(k-1)}}{(x_i - x_{i-k})(y_j - y_{j-k})} & \text{if } (i > k-1 \wedge j > k-1 \wedge i+j \leq n) \end{cases} \quad (2.3)$$

The n^{th} -order table of divided differences is given by

$$\begin{array}{c|cccc} & x_0 & x_1 & x_2 & \cdots & x_n \\ \hline y_0 & P_{0,0}^{(0)} & P_{1,0}^{(1)} & P_{2,0}^{(2)} & \cdots & P_{n,0}^{(n)} \\ y_1 & P_{0,1}^{(1)} & P_{1,1}^{(1)} & \cdots & & P_{n-1,1}^{(n-1)} \\ y_2 & P_{0,2}^{(2)} & \vdots & \ddots & & \\ \vdots & \vdots & P_{1,n-1}^{(n-1)} & & & \\ y_n & P_{0,n}^{(n)} & & & & \end{array} \quad (2.4)$$

since some of the elements of $P_{i,j}^{(k)}$ remain invariant in each step i.e.

$P_{0,0}^{(0)}$ in the 1st step,

$\begin{pmatrix} P_{0,0}^{(0)} & P_{1,0}^{(1)} \\ P_{0,1}^{(1)} & P_{1,1}^{(1)} \end{pmatrix}$ in the 2nd step,

.....
 $\begin{pmatrix} P_{0,0}^{(0)} & P_{1,0}^{(1)} & \cdots & P_{n-1,0}^{(n-1)} \\ P_{0,1}^{(1)} & P_{1,1}^{(1)} & \cdots & P_{n-1,1}^{(n-1)} \\ \vdots & \vdots & \ddots & \vdots \\ P_{0,n-1}^{(n-1)} & P_{1,n-1}^{(n-1)} & \cdots & 0 \end{pmatrix}$ in the n^{th} step.

Therefore, we do not need to re-compute these terms in each step, by saving a lot of computations during the algorithm.

Step 3: The Newton interpolating polynomial is given by the following formula:

$$P_n(x, y) = Y^T A X \quad (2.5)$$

where

$$A = \begin{pmatrix} P_{0,0}^{(0)} & P_{1,0}^{(1)} & \cdots & P_{n,0}^{(n)} & P_{n,0}^{(n)} \\ P_{0,1}^{(1)} & P_{1,1}^{(1)} & \cdots & P_{n-1,1}^{(n-1)} & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ P_{0,n-1}^{(n-1)} & P_{1,n-1}^{(n-1)} & \cdots & 0 & 0 \\ P_{0,n}^{(n)} & 0 & 0 & 0 & 0 \end{pmatrix} \quad (2.6a)$$

$$X = \begin{pmatrix} 1 \\ x - x_0 \\ (x - x_0)(x - x_1) \\ \vdots \\ (x - x_0)(x - x_1) \cdots (x - x_{n-1}) \end{pmatrix} \in \mathbb{R}[x]^{(n+1) \times 1} \quad (2.6b)$$

$$Y = \begin{pmatrix} 1 \\ y - y_0 \\ (y - y_0)(y - y_1) \\ \vdots \\ (y - y_0)(y - y_1) \cdots (y - y_{n-1}) \end{pmatrix} \in \mathbb{R}[y]^{(n+1) \times 1} \quad (2.6c) \quad \blacksquare$$

Example 1 Let us find a 3rd order two-variable Newton interpolating polynomial $P_3(x, y) = \sum_{i=0}^3 \sum_{j=0}^{3-i} a_{i,j} x^i y^j$ of a function $f(x, y)$. The number of nodes we need is $\binom{3+2}{3} = \frac{5!}{3!(5-3)!} = 10$. Let these nodes,

$$P_3(x_i, y_j) = P_{i,j}^{(0)} = f(x_i, y_j)$$

for $i = 0(1)3$, $j = 0(1)3$ and $i + j \leq 3$, given by the following table :

$f(x_i, y_j)$	$x_0 = 0$	$x_1 = 1$	$x_2 = 2$	$x_3 = 3$
$y_0 = 0$	-2	-4	-6	-8
$y_1 = 1$	-2	8	48	
$y_2 = 2$	-2	20		
$y_3 = 3$	-2			

Applying Algorithm 1, we get:

Step 1: Construct the 0th-order table of initial values

	$x_0 = 0$	$x_1 = 1$	$x_2 = 2$	$x_3 = 3$
$y_0 = 0$	$P_{0,0}^{(0)} = -2$	$P_{1,0}^{(0)} = -4$	$P_{2,0}^{(0)} = -6$	$P_{3,0}^{(0)} = -8$
$y_1 = 1$	$P_{0,1}^{(0)} = -2$	$P_{1,1}^{(0)} = 8$	$P_{2,1}^{(0)} = 48$	
$y_2 = 2$	$P_{0,2}^{(0)} = -2$	$P_{1,2}^{(0)} = 20$		
$y_3 = 3$	$P_{0,3}^{(0)} = -2$			

Step 2: For $k=1(1)3$, compute the kth-order table of divided differences given by the recursive form (2.3).

For $k=1$ the 1st order table of divided differences is given by:

	$x_0 = 0$	$x_1 = 1$	$x_2 = 2$	$x_3 = 3$
$y_0 = 0$	$P_{0,0}^{(1)} = -2$	$P_{1,0}^{(1)} = -2$	$P_{2,0}^{(1)} = -2$	$P_{3,0}^{(1)} = -2$
$y_1 = 1$	$P_{0,1}^{(1)} = 0$	$P_{1,1}^{(1)} = 12$	$P_{2,1}^{(1)} = 42$	
$y_2 = 2$	$P_{0,2}^{(1)} = 0$	$P_{1,2}^{(1)} = 12$		
$y_3 = 3$	$P_{0,3}^{(1)} = 0$			

Note that the value in bold of $P_{0,0}^{(0)}$ in (2.9) is the same with the ones in (2.8), and therefore we only need **9 computations** for the values of $P_{i,j}^{(1)}$.

For $k=2$ the 2nd order table of divided differences is given by:

	$x_0 = 0$	$x_1 = 1$	$x_2 = 2$	$x_3 = 3$
$y_0 = 0$	$P_{0,0}^{(2)} = -2$	$P_{1,0}^{(2)} = -2$	$P_{2,0}^{(2)} = 0$	$P_{3,0}^{(2)} = 0$
$y_1 = 1$	$P_{0,1}^{(2)} = 0$	$P_{1,1}^{(2)} = 12$	$P_{2,1}^{(2)} = 15$	
$y_2 = 2$	$P_{0,2}^{(2)} = 0$	$P_{1,2}^{(2)} = 0$		
$y_3 = 3$	$P_{0,3}^{(2)} = 0$			

Note also that the values in bold of $P_{0,0}^{(0)}, P_{1,0}^{(1)}, P_{0,1}^{(1)}, P_{1,1}^{(1)}$ in (2.10) are the same with the ones in (2.9), and therefore we only need **6 computations** for the values of $P_{i,j}^{(2)}$.

For $k=3$ the 3rd order table of divided differences is given by:

	$x_0 = 0$	$x_1 = 1$	$x_2 = 2$	$x_3 = 3$
$y_0 = 0$	$P_{0,0}^{(3)} = -2$	$P_{1,0}^{(3)} = -2$	$P_{2,0}^{(3)} = 0$	$P_{3,0}^{(3)} = 0$
$y_1 = 1$	$P_{0,1}^{(3)} = 0$	$P_{1,1}^{(3)} = 12$	$P_{2,1}^{(3)} = 15$	
$y_2 = 2$	$P_{0,2}^{(3)} = 0$	$P_{1,2}^{(3)} = 0$		
$y_3 = 3$	$P_{0,3}^{(3)} = 0$			

Note also that the values in bold on the above matrix are the same with the ones in (2.10), and therefore we only need **2 computations** for the values of $P_{i,j}^{(3)}$.

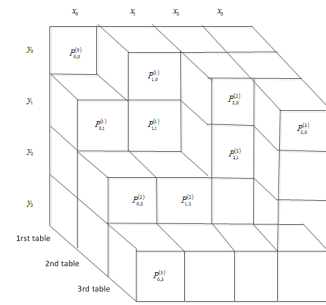


Fig.2 Values that remain invariants in the next steps.

Therefore, the total computations that we need for the construction of the final matrix are $9+6+2=17$.

Step 3: The Newton interpolating polynomial is the following:

$$P_3(x, y) = Y^T A X = -2 - 2x - 3xy + 15x^2y$$

where

$$A = \begin{pmatrix} P_{0,0}^{(0)} = -2 & P_{1,0}^{(1)} = -2 & P_{2,0}^{(2)} = 0 & P_{3,0}^{(3)} = 0 \\ P_{0,1}^{(1)} = 0 & P_{1,1}^{(1)} = 12 & P_{2,1}^{(2)} = 15 & 0 \\ P_{0,2}^{(2)} = 0 & P_{1,2}^{(2)} = 0 & 0 & 0 \\ P_{0,3}^{(3)} = 0 & 0 & 0 & 0 \end{pmatrix}$$

and

$$X = \begin{pmatrix} 1 \\ x \\ x(x-1) \\ x(x-1)(x-2) \end{pmatrix}; \quad Y = \begin{pmatrix} 1 \\ y \\ y(y-1) \\ y(y-1)(y-2) \end{pmatrix}$$

■

III. INTERPOLATING BIVARIATE POLYNOMIALS WITH KNOWN DEGREES IN TERMS OF EACH VARIABLE

The previous section has focused on the computation of a n^{th} order Newton two-variable interpolating polynomial for a function $f(x, y)$. In this section, we are considering the special case where the function $f(x, y)$ is a two-variable polynomial $p(x, y)$ with known upper bounds on the degrees in terms of x and y (let k_1 and k_2 respectively) i.e.

$$f(x, y) \equiv p(x, y) = \sum_{i=0}^{k_1} \sum_{j=0}^{k_2} a_{i,j} x^i y^j \quad (3.1)$$

The total order of $p(x, y)$ is $n = k_1 + k_2$. Therefore, according to Algorithm 1, we can approximate it, by a n^{th} order Newton two-variable interpolating polynomial

$$P_n(x, y) = \sum_{i=0}^n \sum_{j=0}^{n-i} a_{i,j} x^i y^j \quad (3.2)$$

if we know its values at a set

$$S_\Delta^n = \left\{ (x_i, y_j) \mid i, j \geq 0, i + j \leq n \right\}$$

$$\text{of } N = \binom{n+2}{n} = \frac{(n+2)!}{n!2!} = \frac{(k_1 + k_2 + 2)!}{(k_1 + k_2)!2!} \text{ points.}$$

Consider the matrices Y, A and X defined in (2.6) :

$$A = \begin{pmatrix} A_{1,1} & A_{1,2} \\ A_{2,1} & A_{2,2} \end{pmatrix} = \begin{pmatrix} \mathbf{P}_{0,0}^{(n)} & \mathbf{P}_{1,0}^{(n)} & \mathbf{P}_{2,0}^{(n)} & \dots & \mathbf{P}_{k_1,0}^{(n)} & \dots & \mathbf{P}_{n,0}^{(n)} \\ \mathbf{P}_{0,1}^{(n)} & \mathbf{P}_{1,1}^{(n)} & \dots & \dots & \vdots & \dots & \mathbf{P}_{n-1,1}^{(n)} \\ \mathbf{P}_{0,2}^{(n)} & \vdots & \dots & \dots & \vdots & \dots & \vdots \\ \vdots & \vdots & \dots & \dots & \vdots & \dots & \vdots \\ \mathbf{P}_{0,k_2}^{(n)} & \dots & \dots & \dots & \mathbf{P}_{k_1,k_2}^{(n)} & \dots & \vdots \\ \vdots & \dots & \dots & \dots & \vdots & \dots & \vdots \\ \vdots & \dots & \dots & \dots & \vdots & \dots & \vdots \\ \mathbf{P}_{0,n}^{(n)} & \dots & \dots & \dots & \vdots & \dots & \vdots \end{pmatrix} \quad (3.3a)$$

$$X = \begin{pmatrix} \mathbf{X}_1 \\ \mathbf{X}_2 \end{pmatrix} = \begin{pmatrix} I \\ \mathbf{x} - \mathbf{x}_0 \\ \vdots \\ (\mathbf{x} - \mathbf{x}_0)(\mathbf{x} - \mathbf{x}_1) \cdots (\mathbf{x} - \mathbf{x}_{k_1-1}) \\ \vdots \\ (\mathbf{x} - \mathbf{x}_0)(\mathbf{x} - \mathbf{x}_1) \cdots (\mathbf{x} - \mathbf{x}_{n-1}) \end{pmatrix} \quad (3.3b)$$

$$Y = \begin{pmatrix} \mathbf{Y}_1 \\ \mathbf{Y}_2 \end{pmatrix} = \begin{pmatrix} I \\ \mathbf{y} - \mathbf{y}_0 \\ \vdots \\ (\mathbf{y} - \mathbf{y}_0)(\mathbf{y} - \mathbf{y}_1) \cdots (\mathbf{y} - \mathbf{y}_{k_2-1}) \\ \vdots \\ (\mathbf{y} - \mathbf{y}_0)(\mathbf{y} - \mathbf{y}_1) \cdots (\mathbf{y} - \mathbf{y}_{n-1}) \end{pmatrix} \quad (3.3c)$$

Then

$$P_n(x, y) = (\mathbf{Y}_1 \quad \mathbf{Y}_2) \begin{pmatrix} A_{1,1} & A_{1,2} \\ A_{2,1} & 0_{2,2} \end{pmatrix} \begin{pmatrix} \mathbf{X}_1 \\ \mathbf{X}_2 \end{pmatrix} = \mathbf{Y}_1^T A_{1,1} \mathbf{X}_1 + \mathbf{Y}_2^T A_{2,1} \mathbf{X}_1 + \mathbf{Y}_1^T A_{1,2} \mathbf{X}_2 \quad (3.4)$$

The coefficients of y^j with $j > k_2 - 1$ in the following term

$$\mathbf{Y}_2^T A_{2,1} \mathbf{X}_1 = \left((y - y_0) \times \dots \times (y - y_{k_2}) \quad \dots \quad (y - y_0) \times \dots \times (y - y_{k_1+k_2-1}) \right) \times \begin{pmatrix} \mathbf{P}_{0,k_2+1}^{(n)} & \mathbf{P}_{1,k_2+1}^{(n)} & \dots & \mathbf{P}_{k_1-1,k_2+1}^{(n)} & 0 \\ \mathbf{P}_{0,k_2+2}^{(n)} & \mathbf{P}_{1,k_2+2}^{(n)} & \dots & \vdots & 0 \\ \vdots & \vdots & \dots & \vdots & \vdots \\ \mathbf{P}_{0,k_1+k_2}^{(n)} & 0 & \dots & \dots & 0 \end{pmatrix} \begin{pmatrix} 1 \\ \mathbf{x} - \mathbf{x}_0 \\ \vdots \\ (\mathbf{x} - \mathbf{x}_0)(\mathbf{x} - \mathbf{x}_1) \cdots (\mathbf{x} - \mathbf{x}_{k_1-1}) \end{pmatrix} \quad (3.5)$$

are equal to zero, since according to our initial assumption the upper bound of the degree in terms of y does not exceed k_2 . Therefore, $\mathbf{P}_{i,j}^{(n)} = 0$ for $i = 0, 1, \dots, k_1$ and $j = k_2 + 1, k_2 + 2, \dots, k_1 + k_2$ ($n = k_1 + k_2$) or equivalently $\mathbf{Y}_2^T A_{2,1} \mathbf{X}_1 = 0$. Similarly, we can show that $\mathbf{P}_{i,j}^{(n)} = 0$ for $i = k_1 + 1, k_1 + 2, \dots, k_1 + k_2$ and $j = 0, 1, \dots, k_2$ ($n = k_1 + k_2$) or equivalently $\mathbf{Y}_1^T A_{1,2} \mathbf{X}_2 = 0$ due to our initial assumption that the upper bound of the degree in terms of x does not exceed k_1 . Thus, the matrix A must have the following form

$$A = \begin{pmatrix} A_{1,1} & 0 \\ 0 & 0 \end{pmatrix} \quad (3.6)$$

and $P_n(x, y)$ is reduced to

$$P_n(x, y) = \mathbf{Y}_1^T A_{1,1} \mathbf{X}_1 \quad (3.7)$$

Therefore, in order to compute $A_{1,1}$ we need only $(k_1+1)(k_2+1)$ of the $N = (k_1+k_2+1)(k_1+k_2+2)/2$ initial values of $p(x,y)$ i.e. $(k_1+k_1^2+k_2+k_2^2)/2$ less values. In case where these values are coming from complex computations i.e. the determinant of a two-variable matrix at these specific initial values, then we save a lot of computations from the very beginning.

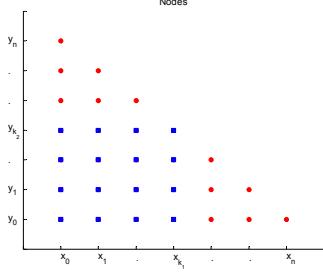


Fig. 3. An example of the set S_{Δ}^n (red and blue) and the set points we actually need (in blue).

Based on the above results, Algorithm 1 can be reduced to the next less consuming in speed and memory algorithm.

Algorithm 2. Construction of a Newton interpolating two-variable polynomial $P_n(x,y)$ (defined in (3.2)) for a two-variable polynomial $p(x,y)$ with upper bound on the degree of x (resp. y) k_1 (resp. k_2).

Step 1: $k=0$. Based on the values of $p(x,y)$ at the set of points $\tilde{S}_{\Delta}^n = \{(x_i, y_j) | i=0,1,\dots,k_1, j=0,1,\dots,k_2\}$, create the k^{th} -order table of initial values $P_{i,j}^{(0)} := p(x_i, y_j)$

$$\begin{array}{c}
 \begin{array}{cccccc}
 x_0 & x_1 & x_2 & \cdots & x_{k_1} \\
 y_0 & \begin{array}{c} P_{0,0}^{(0)} \\ P_{0,1}^{(0)} \\ P_{0,2}^{(0)} \\ \vdots \\ P_{0,k_2}^{(0)} \end{array} & \begin{array}{c} P_{1,0}^{(0)} \\ P_{1,1}^{(0)} \\ P_{1,2}^{(0)} \\ \vdots \\ P_{1,k_2}^{(0)} \end{array} & \begin{array}{c} P_{2,0}^{(0)} \\ P_{2,1}^{(0)} \\ P_{2,2}^{(0)} \\ \vdots \\ P_{2,k_2}^{(0)} \end{array} & \cdots & \begin{array}{c} P_{k_1,0}^{(0)} \\ P_{k_1,1}^{(0)} \\ P_{k_1,2}^{(0)} \\ \vdots \\ P_{k_1,k_2}^{(0)} \end{array} \\
 y_1 & & & & & \\
 y_2 & & & & & \\
 \vdots & & & & & \\
 y_{k_2} & & & & &
 \end{array}
 \end{array}
 \quad (3.8)$$

Step 2: For $k=1(1)\tilde{n}$, where $\tilde{n} = \max\{k_1, k_2\}$ compute the \tilde{n}^{th} -order table of divided differences given by the recursive form (2.3)

$$\begin{array}{c}
 \begin{array}{cccccc}
 x_0 & x_1 & x_2 & \cdots & x_{k_1} \\
 y_0 & \begin{array}{c} P_{0,0}^{(\tilde{n})} \\ P_{0,1}^{(\tilde{n})} \\ P_{0,2}^{(\tilde{n})} \\ \vdots \\ P_{0,k_2}^{(\tilde{n})} \end{array} & \begin{array}{c} P_{1,0}^{(\tilde{n})} \\ P_{1,1}^{(\tilde{n})} \\ P_{1,2}^{(\tilde{n})} \\ \vdots \\ P_{1,k_2}^{(\tilde{n})} \end{array} & \begin{array}{c} P_{2,0}^{(\tilde{n})} \\ P_{2,1}^{(\tilde{n})} \\ P_{2,2}^{(\tilde{n})} \\ \vdots \\ P_{2,k_2}^{(\tilde{n})} \end{array} & \cdots & \begin{array}{c} P_{k_1,0}^{(\tilde{n})} \\ P_{k_1,1}^{(\tilde{n})} \\ P_{k_1,2}^{(\tilde{n})} \\ \vdots \\ P_{k_1,k_2}^{(\tilde{n})} \end{array} \\
 y_1 & & & & & \\
 y_2 & & & & & \\
 \vdots & & & & & \\
 y_{k_2} & & & & &
 \end{array}
 \end{array}
 \quad (3.9)$$

which coincides for example in case where $\tilde{n} = k_1 > k_2$

with the matrix

$$\begin{array}{c}
 \begin{array}{cccccc}
 x_0 & x_1 & x_2 & \cdots & x_{k_2} & \cdots & x_{k_1} \\
 y_0 & \begin{array}{c} P_{0,0}^{(0)} \\ P_{0,1}^{(1)} \\ P_{0,2}^{(2)} \\ \vdots \\ P_{0,k_2}^{(k_2)} \end{array} & \begin{array}{c} P_{1,0}^{(1)} \\ P_{1,1}^{(1)} \\ P_{1,2}^{(2)} \\ \vdots \\ P_{1,k_2}^{(k_2)} \end{array} & \begin{array}{c} P_{2,0}^{(2)} \\ P_{2,1}^{(2)} \\ P_{2,2}^{(2)} \\ \vdots \\ P_{2,k_2}^{(k_2)} \end{array} & \cdots & \begin{array}{c} P_{k_2,0}^{(k_2)} \\ P_{k_2,1}^{(k_2)} \\ P_{k_2,2}^{(k_2)} \\ \vdots \\ P_{k_2,k_2}^{(k_2)} \end{array} & \cdots & \begin{array}{c} P_{k_1,0}^{(k_1)} \\ P_{k_1,1}^{(k_1)} \\ P_{k_1,2}^{(k_1)} \\ \vdots \\ P_{k_1,k_2}^{(k_1)} \end{array} \\
 y_1 & & & & & & & \\
 y_2 & & & & & & & \\
 \vdots & & & & & & & \\
 y_{k_2} & & & & & & &
 \end{array}
 \end{array}$$

Step 3: The Newton interpolating polynomial is the following :

$$P_n(x,y) \equiv p(x,y) = Y_1^T A_{1,1} X_1 \quad (3.10)$$

where $Y_1, A_{1,1}, X_1$ have been defined in (3.3). ■

Let us assume that in order to compute

$$\frac{P_{i,j}^{(k-1)} - P_{i-1,j}^{(k-1)}}{x_i - x_{i-k}} \quad \text{or} \quad \frac{P_{i,j}^{(k-1)} - P_{i,j-1}^{(k-1)}}{y_j - y_{j-k}} \quad (3.11)$$

in (2.3) we need a operations (2 additions and 1 multiplication), whereas for

$$\frac{P_{i,j}^{(k-1)} + P_{i-1,j-1}^{(k-1)} - P_{i,j-1}^{(k-1)} - P_{i-1,j}^{(k-1)}}{(x_i - x_{i-k})(y_j - y_{j-k})} \quad (3.12)$$

we need b operations (5 additions and 2 multiplications).

Complexity of Algorithm 1.

The computation of the first-order table, requires na operations for the first row, na operations for the first

column and $\frac{n(n-1)}{2}b$ operations for the rest elements.

Thus, the total number of operations is

$$s_1 = 2na + \frac{n(n-1)}{2}b \quad \text{or} \quad s_1 = 2(S_n - S_{n-1})a + S_{n-1}b \quad \text{where}$$

S_n the sum of arithmetic progression with $a_1=1$ and $d=1$.

The computation of the second-order table, requires $[(n-1)+(n-2)]a$ operations for the first and second row

and $[(n-1)+(n-2)]a$ operations for the first and second column, since the elements in

$$\begin{pmatrix} P_{0,0}^{(0)} & P_{1,0}^{(1)} \\ P_{0,1}^{(1)} & P_{1,1}^{(1)} \end{pmatrix}$$

remain invariant and $\left(\frac{(n-2)(n-3)}{2}\right)b$ operations for the rest elements. Thus, the total number of operations is $s_2 = 2[(n-1)(n-2)]a + \left(\frac{(n-2)(n-3)}{2}\right)b$ or

$$s_2 = 2(S_{n-1} - S_{n-3})a + S_{n-3}b.$$

Finally, the computation of the n^{th} -order table, requires a operations for the n first rows and a operations for the n first columns, since the elements in

$$\begin{pmatrix} P_{0,0}^{(0)} & P_{1,0}^{(1)} & \dots & P_{n-1,0}^{(n-1)} \\ P_{0,1}^{(1)} & P_{1,1}^{(1)} & \dots & P_{n-1,1}^{(n-1)} \\ \vdots & \vdots & \ddots & \vdots \\ P_{0,n-1}^{(n-1)} & P_{1,n-1}^{(n-1)} & \dots & 0 \end{pmatrix}$$

remain invariant and no one operation for the rest elements. Thus, the total number of operations is $s_n = 2a$ or $s_n = 2S_1a$.

Steps	Operations
s_1	$2(S_n - S_{n-1})a + S_{n-1}b$
s_2	$2(S_{n-1} - S_{n-3})a + S_{n-3}b$
....
s_n	$2S_1a$

Thus, the total operations for Algorithm 1, are given by

$$s = \sum_{i=1}^n s_i = [2(S_n - S_{n-1})a + S_{n-1}b] + [2(S_{n-1} - S_{n-3})a + S_{n-3}b] + \dots + [2S_1a]$$

or equivalently by

$$s = \frac{1}{24}n(n+2)[2(2n+5)a + (2n-1)b]$$

if n is even, and

$$s = \frac{1}{24}(n+1)[2(n+3)(2n+1)a + (n-1)(2n+3)b]$$

if n is odd.

Therefore, the total complexity is $O(n^3)$ or equivalently $O((k_1 + k_2)^3)$ (apart from Step 1).

Complexity of Algorithm 2.

The computation of the first-order table, requires k_1a operations for the first row, k_2a operations for the first column and k_1k_2b operations for the rest elements. Thus, the total number of operations is $s_1 = (k_1 + k_2)a + k_1k_2b$.

The computation of the second-order table requires $2(k_1-1)a$ operations for the first and second row, $2(k_2-1)a$ operations for the first and second column and $(k_1-1)(k_2-1)b$ operations for the rest elements. Thus, the total number of operations is $s_2 = 2(k_1-1)2(k_2-1)a + (k_1-1)(k_2-1)b$.

Under the assumption that $k_1 > k_2$ the computation of the k_2 -order table, requires $k_2(k_1+1-k_2)a$ operations for the k_2 first rows, k_2a operations for the k_2 first columns and $(k_1+1-k_2)b$ operations for the rest elements. Thus, the total number of operations is $s_{k_2} = k_2(k_1+1-k_2)a + k_2a + (k_1+1-k_2)b$.

Finally, the computation of the divided-differences of the k_1^{th} order table, requires $(k_2+1)a$ operations for the (k_2+1) first rows, and no one operation for the rest elements. Thus, the total number of operations is $s_{k_1} = (k_2+1)a$.

Steps	Operations
s_1	$(k_1 + k_2)a + k_1k_2b$
s_2	$2(k_1 - 1)2(k_2 - 1)a + (k_1 - 1)(k_2 - 1)b$
....
s_{k_2}	$k_2(k_1 + 1 - k_2)a + k_2a + (k_1 + 1 - k_2)b$
...
s_{k_1}	$(k_2 + 1)a$

Thus, the total operations for Algorithm 2, are given by

$$s = \sum_{i=1}^{\bar{n}} s_i = [(k_1 + k_2)a + k_1k_2b] + [2(k_1-1)2(k_2-1)a + (k_1-1)(k_2-1)b] + \dots + [k_2(k_1+1-k_2)a + k_2a + (k_1+1-k_2)b] + \dots + [(k_2+1)a]$$

or equivalently by

$$s = \frac{a}{6}(k_2+1)(3k_1+k_2+3k_1^2-3k_1k_2+2k_2^2) + \frac{b}{6}(k_2+3k_1k_2+3k_1k_2^2-k_2^3)$$

The worst case is when $k_1 = k_2$. In that case the total number of computations is

$$s = a \frac{(4k_1 + 2k_1^2)(k_1 + 1)}{6} + b \left(\frac{k_1 + 3k_1^2 + 2k_1^3}{6} \right)$$

and therefore, the worst case complexity is $O(k_1^3)$.

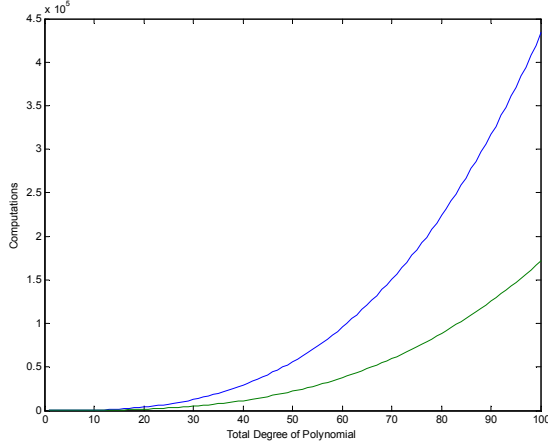


Fig. 5. The total number of operations (if $a=1$ and $b=2$) in step 2 of Algorithm 1 (blue) and Algorithm 2 (green) when $k_1 = k_2$.

Example 2. Consider the Example 1. Suppose that we know from the beginning that the polynomial $p(x, y)$ that we are looking for, has an upper bound 2 (resp. 1) for the degree in terms of x (resp. y) i.e. $k_1 = 2$, $k_2 = 1$ and $n = 2 + 1 = 3$. In order to approximate $p(x, y)$ with a 3rd order polynomial $P_3(x, y)$, we have to know its values at a set

$$S_{\Delta}^3 = \left\{ (x_i, y_j) \mid i, j \geq 0, i + j \leq 3 \right\}$$

of $N = \binom{3+2}{3} = 10$ points. However, according to the above theory and the results of Example 1, we have that:

Step 1: We create the table of initial values

$$\begin{array}{c} x_0 = 0 \quad x_1 = 1 \quad x_2 = 2 \\ y_0 = 0 \quad \begin{array}{|c|c|c|} \hline P_{0,0}^{(0)} = -2 & P_{1,0}^{(0)} = -4 & P_{2,0}^{(0)} = -6 \\ \hline \end{array} \\ y_1 = 1 \quad \begin{array}{|c|c|c|} \hline P_{0,1}^{(0)} = -2 & P_{1,1}^{(0)} = 8 & P_{2,1}^{(0)} = 48 \\ \hline \end{array} \end{array}$$

Step 2: Compute k^{th} order divided differences according to the recursive form (2.3).

For $k=1$ the 1st order table of divided differences is

$$\begin{array}{c} x_0 = 0 \quad x_1 = 1 \quad x_2 = 2 \\ y_0 = 0 \quad \begin{array}{|c|c|c|} \hline P_{0,0}^{(1)} = -2 & P_{1,0}^{(1)} = -2 & P_{2,0}^{(1)} = -2 \\ \hline \end{array} \\ y_1 = 1 \quad \begin{array}{|c|c|c|} \hline P_{0,1}^{(1)} = 0 & P_{1,1}^{(1)} = 12 & P_{2,1}^{(1)} = 42 \\ \hline \end{array} \end{array}$$

For $k=2$ the 2nd order table of divided differences is

$$\begin{array}{c} x_0 = 0 \quad x_1 = 1 \quad x_2 = 2 \\ y_0 = 0 \quad \begin{array}{|c|c|c|} \hline P_{0,0}^{(2)} = -2 & P_{1,0}^{(2)} = -2 & P_{2,0}^{(2)} = 0 \\ \hline \end{array} \\ y_1 = 1 \quad \begin{array}{|c|c|c|} \hline P_{0,1}^{(2)} = 0 & P_{1,1}^{(2)} = 12 & P_{2,1}^{(2)} = 15 \\ \hline \end{array} \end{array}$$

Step 3: The interpolating polynomial is :

$$p(x, y) = P_3(x, y) = Y_1^T A_{1,1} X_1 = -2 - 2x - 3xy + 15x^2y$$

where

$$A_{1,1} = \begin{pmatrix} P_{0,0}^{(0)} = -2 & P_{1,0}^{(0)} = -2 & P_{2,0}^{(0)} = 0 \\ P_{0,1}^{(0)} = 0 & P_{1,1}^{(0)} = 12 & P_{2,1}^{(0)} = 15 \end{pmatrix}$$

and

$$X_1 = \begin{pmatrix} 1 \\ x \\ x(x-1) \end{pmatrix}; \quad Y_1 = \begin{pmatrix} 1 \\ y \end{pmatrix}$$

In order to compute the matrix $A_{1,1}$ we need to evaluate $(k_1 + 1)(k_2 + 1) = 3 \times 2 = 6$ initial values of $p(x, y)$, instead of 10 in Algorithm 1. The total number of operations in Step 2 is 7 instead of 17 in Algorithm 1. Finally, in Step 3 we have a multiplication of 3 matrices with dimensions $(1 \times 2)(2 \times 3)(3 \times 1)$ instead of $(1 \times 4)(4 \times 4)(4 \times 1)$ in Algorithm 1.

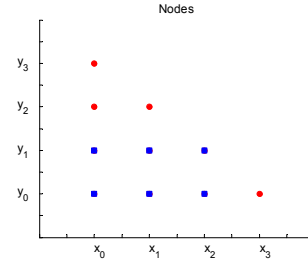


Fig. 4. An example of the set S_{Δ}^3 (red and blue) and the set points we actually need (in blue).

IV. ON THE COMPUTATION OF THE DETERMINANT OF A TWO-VARIABLE POLYNOMIAL MATRIX

In this section we apply Algorithm 2 for the computation of a two-variable polynomial matrix.

Let the polynomial matrix

$$A(x, y) = \begin{pmatrix} -1 & 0 & x \\ 5 & 1 & -1 \\ 2 & 3xy & 2 \end{pmatrix}$$

Step 0: We compute the upper bounds on the degree of x (resp. y) k_1 (resp. k_2) in $p(x, y) = \det A(x, y)$. Since the greatest degree in terms of x of each column of the matrix is 0, 1 and 1 respectively, then $k_1 = 0 + 1 + 1 = 2$. Working in the same way for y we have that $k_2 = 0 + 1 + 0 = 1$.

Step 1: We create the table of initial values $P_{i,j}^{(0)} := p(x_i, y_j) = \det A(x_i, y_j)$:

$$\begin{array}{c} x_0 = 0 \quad x_1 = 1 \quad x_2 = 2 \\ y_0 = 0 \quad \left[\begin{array}{ccc} P_{0,0}^{(0)} = -2 & P_{1,0}^{(0)} = -4 & P_{2,0}^{(0)} = -6 \\ P_{0,1}^{(0)} = -2 & P_{1,1}^{(0)} = 8 & P_{2,1}^{(0)} = 48 \end{array} \right. \\ y_1 = 1 \end{array}$$

which is the same with the ones of Example 1.

Since the computation of the determinant of a constant matrix $A \in \mathbb{R}^{\ell \times \ell}$ by using the Gauss method requires $O(\ell^3)$ operations, the computation of initial values needs $O(R\ell^3)$ operations where $R = (k_1 + 1)(k_2 + 1)$. The first step is similar to the ones used by [9] with the only difference that DFT methods are using specific points (x_i, y_j) with x_i, y_j belonging to the unit circle. Thus, on the DFT methods we don't need to evaluate all the initial values. Apart of this, the complexity of the respective DFT method in [9] is $O(R \log(R))$ in contrast to $O((\max(k_1, k_2))^3)$ in Step 2 of Algorithm 2. Therefore, the DFT method is better than the ones in Algorithm 2.

Step 2: For $k=1(1)n$, compute the k^{th} order table of divided differences according to the recursive form (2.3). All the tables are given in Example 2 i.e. the 3rd order table is given by

$$\begin{array}{c} x_0 = 0 \quad x_1 = 1 \quad x_2 = 2 \\ y_0 = 0 \quad \left[\begin{array}{ccc} P_{0,0}^{(0)} = -2 & P_{1,0}^{(0)} = -2 & P_{2,0}^{(0)} = 0 \\ P_{0,1}^{(0)} = 0 & P_{1,1}^{(0)} = 12 & P_{2,1}^{(0)} = 15 \end{array} \right. \\ y_1 = 1 \end{array}$$

Step 3: Compute the interpolating polynomial in Newton form according to the following form

$$p(x, y) = P_3(x, y) = Y_1^T A_{1,1} X_1 = -2 - 2x - 3xy + 15x^2y$$

where the matrices $Y_1, A_{1,1}, X_1$ have been defined in Example 2.

V. CONCLUSION

A modification of the Newton divided-difference algorithm [11] for the special case of two-variable polynomials has been given. The complexity of this new algorithm has proved that it is better than the ones given in [11]. The reason is twofold: a) it uses less interpolation points and b) it doesn't need to re-compute elements that remain invariant in each step of the algorithm. The proposed algorithm has been tested on the computation of the determinant of a two-variable polynomial matrix, and thus providing a different way of approximation from the

known ones in [9] and [17]. Further applications of this algorithm might be the computation of : a) the transfer function of two-variable systems, b) the solution of polynomial matrix Diophantine equations, and c) the generalized inverse of two-variable polynomial matrices. Following similar lines, the proposed algorithm can be extended to more variables than two.

REFERENCES

- [1] Antoniou E. G., 2001, Transfer Function Computation for Generalized Ndimensional Systems, Journal of the Franklin Institute, vol. 338, pp. 83-90.
- [2] de Boor, C., and Ron, A., On multivariate polynomial interpolation, Constr. Approx. 6 (1990), 287-302.
- [3] de Boor, C., A multivariate divided difference, in: Approximation theory VIII, Vol. 1, C.K. Chui and L.L. Schumaker, eds., World Sci. Publishing, River Edge, NJ, 1995, pp. 87-96.
- [4] Gasca M. and Martinez Jose J., 1992, Bivariate Hermite-Birkhoff interpolation and Vandermonde determinants. Numerical Algorithms, 2, 193-199.
- [5] Gasca M. and Sauer T., Polynomial interpolation in several variables, Advances in Computational Math. 12 (2000), 377-410.
- [6] Gasca M. and Sauer T., 2000, On the history of multivariate polynomial interpolation. Numerical analysis 2000, Vol. II: Interpolation and extrapolation. J. Comput. Appl. Math., 122, no. 1-2, 23-35.
- [7] Hromcik M. and Sebek M., 2001, Fast Fourier Transform and Linear Polynomial Matrix Equations, Proceedings of the 1st IFAC Workshop on Systems Structure and Control, Prague, Czech Republic.
- [8] Karampetakis N.P., Vologianidis S., 2003, DFT calculation of the generalized and Drazin inverse of a polynomial matrix, Applied Mathematics and Computation, 143, 501-521.
- [9] Karampetakis N. P. and Evripidou A., 2010, On the computation of the inverse of a two-variable polynomial matrix by interpolation, Multidim Syst Sign Process, DOI 10.1007/s11045-010-0102-7.
- [10] Lipson John D., 1976, The Fast Fourier Transform, Its role as an Algebraic Algorithm. Proceedings of the ACM Annual Conference/Annual Meeting, 436-441.
- [11] Neidinger R. D., Multivariable Interpolating Polynomials in Newton Forms, Joint Mathematics Meetings 2009, Washington D.C., January 5-8, 2009.
- [12] Olver P. J., On Multivariate Interpolation, Studies in Applied Math., 116 (2006) 201-240.
- [13] Paccagnella L. E. and Pierobon G. L., 1976, FFT Calculation of a Determinantal Polynomial, IEEE Trans. Automatic Control, 29, Issue 3, 401-402.
- [14] Philips G. M., 2003, Interpolation and approximation by polynomials, Springer-Verlag.
- [15] Sauer T. and Xu Y., On multivariate Lagrange interpolation, Mathematics of Computation 64 (1995) 1147-1170.
- [16] Schuster A. and Hippe P., 1992, Inversion of polynomial matrices by interpolation, IEEE Transactions on Automatic Control, 37, 363-365.
- [17] Vologianidis S. and Karampetakis N.P., 2004, Inverses of Multivariable Polynomial Matrices by Discrete Fourier Transforms, Multidimensional Systems and Signal Processing, 15, 341-361.