# Real root isolation for univariate polynomials on GPUs and multicores

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# **University of Western Ontario**

#### Direction of the research activities of Marc Moreno Maza's team :

- Study theoretical aspects of systems of polynomial equations and try to answer the question "what is the best form for the set of solutions?"
- Study algorithmic answers to the question "how can we compute this form of the set of solutions at the lowest cost?"
- Study implementation techniques for algorithms to make the best use of today's computers.
- Apply it to unsolved problems when the prototype solver is ready.

## Main purpose of the Lab

The laboratory works in close cooperation with Maplesoft.



Maple 16

#### Current main purpose of the laboratory:

- Provide Maple's end-users with symbolic computation tools.
- Take advantage of hardware acceleration technologies, using GPUs and multicores, using the best computer ressources.
- Develop the library *cumodp* which will be integrated into Maple so as to provide fast arithmetic operations over prime fields.

# Purpose of my internship

- contribute to the library cumodp
- develop code for exact calculation of the real roots of univariate polynomials
- use mathematical tools: Descartes' rule of signs, Fast Fourier transform, computing by homomorphic images...
- realize algorithms using GPUs

# Descartes' rule of sign

## Descartes' rule of signs (DRS)

Consider a univariate polynomial  $P \in \mathbb{R}[X]$  and the sequence  $(a_n)$  of its non-zero coefficients. Let c be the number of sign changes of the sequence  $(a_n)$ . Then the number of positive roots of P is at most c.

## Gauss' property

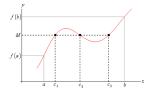
If we consider the previous rule of signs and count the roots with their multiplicities, then the number of positive real roots of P has the same parity as c.

This rule can also be used to determine the number of negative real roots of polynomials.

#### Intermediate values theorem

### Intermediate values theorem (IVT)

If f is a real-valued continuous function on the interval [a, b] and M is a number between f(a) and f(b), then there exists  $c \in [a, b]$  such that we have f(c) = M.



In particular if M=0, then there exists  $c\in [a,b]$  such that f(c)=0 holds.

## Horner's method

Intership context

• We want to evaluate the following polynomial :

$$P(X) = \sum_{i=0}^{n} a_i X^i = a_0 + a_1 X + a_2 X^2 + \dots + a_n X^n$$

A better way to evaluate it is to use Horner's method, that is, represents P in the following form :

$$P(X) = a_0 + X (a_1 + X (a_2 + X (\cdots (a_{n-1} + (a_n X) \cdots))))$$

• <u>costs of operations</u>:  $\Theta(n)$  for Horner's method,  $\Theta(n^2)$  for naive method.

Intership context

## Example of real root search

Let's consider 
$$P(X) = X^3 + 3X^2 - X - 2$$
:  $c = 1$  so  $P$  has 1 positive root.  $P(-X) = -X^3 + 3X^2 + X - 2$ :  $c = 2$  so  $P$  has 2 or 0 negative roots.

$$P(-1) = 1$$
,  $\lim_{X \to -\infty} P(X) = -\infty \Rightarrow \exists r_1 \in ]-\infty; -1[ \mid P(r_1) = 0 \Rightarrow P \text{ has 2 negative roots.}$ 

#### Let's use the IVT for M = 0:

The following evaluations of P can be done using the *Horner's method*.

As 
$$P(-1) = 1$$
 and  $P(-2) = -2$ , then  $r_1 \in ]-2, -1[$ .

As 
$$P(0) = -2$$
 and  $P(-1) = 1$ , then  $r_2 \in ]-1, 0[$ .

As 
$$P(0) = -2$$
 and  $P(1) = 1$ , then  $r_3 \in ]0, 1[$ .

## Vincent-Collins-Akritas' algorithm

The Vincent-Collins-Akritas' algorithm (VCA) computes a list of disjoint intervals with rational endpoints for a polynomial P such that :

- each real root of P belongs to a single interval, and
- each interval contains only one real root of P.

```
Algorithm 1: RealRoots(p)
                                              Algorithm 2: RootsInZeroOne(p)
                                                Input: a univariate squarefree
 Input: a univariate squarefree
         polynomial p of degree d
                                                       polynomial p of degree d
 Output: the number of real roots of
                                                Output: the number of real roots of
                                                         p in (0, 1)
                                             1 begin
2 Let k > 0 be an integer such that
                                             2 p_1 := x^d p(1/x):
     the absolute value of all the real
                                                  p_2 := p_1(x + 1); //Taylor shift
     roots of p is less than or equal to
                                             4 Let v be the number of sign
                                                  variations of the coefficients of p2:
  if x \mid p then m := 1 else m := 0:
                                                 if v \le 1 then return v:
                                                  p_1 := 2^d p(x/2):
    p_2 := p_1(-x);
                                                  p_2 := p_1(x+1): //Taylor shift
    m' := RootsInZeroOne(n_1):
                                                  if x \mid p_2 then m := 1 else m := 0:
    m := m + RootsInZeroOne(p_2);
                                                  m' := RootsInZeroOne(p_1)
s return m + m':
                                                  m := m + RootsInZeroOne(p_2):
                                            11 return m + m':
                                            12 end
```

The algorithm 2 is called several times and inside it, *Taylor shift by* 1 also  $\implies$ : *Taylor shift by* 1 needs to be optimized at the lowest cost possible.

## Modular arithmetic

A current problem : expressions in the coefficients swell when computing with polynomial or matrices over a field ( $\mathbb{Z}$  e.g.)  $\Rightarrow$  performance bottleneck for computer algebra.

#### Two solutions:

- use highly optimized multiprecision libraries (e.g. Gmp), and
- compute by homomorphic images.

#### Ways to compute by homomorphic images:

- use the Chinese Remainder Theorem, or
- use the Hensel's Lemma.

Intership context

# Chinese Remainder Theorem (1)

## Chinese Remainder Theorem 1<sup>st</sup> version (CRT1)

Consider  $m_1, m_2, ..., m_r$  a sequence of r positive integers which are pairwise coprime. Consider also a sequence  $(a_i)$  of integers and the following system (S) of congruence equations:

$$(S): \begin{cases} x \equiv a_1 \mod m_1 \\ x \equiv a_2 \mod m_2 \\ \vdots \\ x \equiv a_r \mod m_r \end{cases}$$

Then (S) has a unique solution modulo  $M=m_1\times m_2\times \cdots \times m_r$ :

$$x = a_1 \times M_1 \times y_1 + a_2 \times M_2 \times y_2 + \cdots + a_r \times M_r \times y_r$$

with 
$$\forall i \in \llbracket 1, r \rrbracket$$
,  $M_i = \frac{M}{m_i}$  and  $y_i \times M_i \equiv 1 \mod m_i$ .

# Chinese Remainder Theorem (2)

#### Lemma

Intership context

Let  $f \in \mathbb{Z}[x]$  be nonzero of degree  $n \in \mathbb{N}$  and  $a \in \mathbb{Z}$ . If the coefficients of f are absolutely bounded by  $B \in \mathbb{N}$ , then the coefficients of  $g = f(x + a) \in \mathbb{Z}[x]$  are absolutely bounded by  $B(|a| + 1)^n$ .

Our future results will be given in  $\mathbb{Z}[x]/M\mathbb{Z}$ . Thanks to lemma, if M is sufficiently big, we could consider our results in  $\mathbb{Z}[x]$ . The algebraic form of the *Chinese Remainder Theorem* will be also used for *homomorphic images*:

## Chinese Remainder Theorem 2<sup>nd</sup> version (CRT2)

Let us consider  $m_1, m_2, ..., m_r$  a sequence of r positive integers which are pairwise coprimes and  $M = m_1 \times m_2 \times \cdots \times m_r$ . Then :

$$\mathbb{Z}/M\mathbb{Z} \cong \mathbb{Z}/m_1\mathbb{Z} \times \mathbb{Z}/m_2\mathbb{Z} \times \cdots \times \mathbb{Z}/m_r\mathbb{Z}$$

# Taylor shift by a

#### Definition

Intership context

The Taylor shift by a of a polynomial  $P \in R[x]$ , with R a field (e.g.,  $\mathbb{Z}$ ) consists of evaluating the coefficients of P(x + a).

So, for a polynomial  $P = \sum_{0 \le i \le n} f_i x^i \in \mathbb{Z}[x]$  and  $a \in \mathbb{Z}$ , we want to compute the coefficients  $g_0,...,g_n \in \mathbb{Z}$  of the Taylor expansion :

$$Q(x) = \sum_{0 \le k \le n} g_k x^k = P(x + a) = \sum_{0 \le i \le n} f_i (x + a)^i$$

There are several methods to compute this, the classical ones deal with the *Horner's method*. There are also asymptotically fast methods, and in particular *Divide & Conquer method (D&C)* which we will use.

# Divide & Conquer method (D&C)

#### **Definition**

The size of a polynomial of degree d is d + 1.

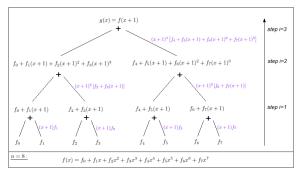
size of the polynomials considered :  $n = 2^e$  (so degree :  $d = 2^e - 1$ )

#### The Divide & Conquer method consists of:

- split the polynomial as :  $P(x) = P^{(0)}(x+1) + (x+1)^{n/2} \times P^{(1)}(x+1)$
- 2 evaluate  $P^{(0)}(x+1)$  and  $P^{(1)}(x+1)$  recursively
- **3** compute a product when  $P^{(1)}(x+1)$  is evaluated
- compute a sum when  $P^{(0)}(x+1)$  and the product are evaluated

These are the four main things to implement to realize the Taylor shift by 1.

## **D&C** tree for $n = 8 = 2^3$



D&C computing tree

In parallel, we consider the tree by levels (from its base) and not recursively.

# Compute the $(x+1)^{2^i}$ s

Intership context

For multiplication, we need to compute the polynomials  $(x+1)^{2^i}$  for  $i \in [0, e-1]$ .

#### Consequence of the binomial theorem

According to the binomial theorem, we have in general:

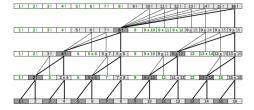
$$\forall n \in \mathbb{N}, (x+1)^n = \sum_{k=0}^n \binom{n}{k} x^k \text{ with } \binom{n}{k} = \frac{n!}{k!(n-k)!}$$

**Consequence**: we need to compute the sequence  $(i!)_{0 \le i \le n}$ .

Intership context

We compute only the sequence  $(i!)_{1 < j < n}$  (power of 2).

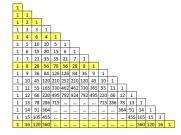
Notation : 
$$a \times b = \prod_{k=a}^{b} k$$
 (e.g.  $9 \times 13 = 9 \times 10 \times 11 \times 12 \times 13$ ).



Mapping of the computation of the sequence  $(i!)_{1 \le i \le 16}$ 

n/2 threads do products using a "pillar" factor (in the darkest boxes). Work :  $\Theta(n \log(n))$ 

# Store the $(x+1)^{2^i}$ s



Pascal triangle

Array Monomial\_shift\_device for  $n = 16 = 2^4$ :

1	1	2	1	4	6	4	1	8	28	56	70	56	28	8	1

At step i,  $local_n = 2^i$ :

$$\forall j \in \llbracket 0, local\_n - 1 
rbracket, Monomial\_shift[local\_n + j] = egin{pmatrix} local\_n \ j + 1 \end{pmatrix}$$

Intership context

# Divide & Conquer method

Recall how we can realize the D&C method.

#### The Divide & Conquer method consists of:

- split the polynomial as :  $P(x) = P^{(0)}(x+1) + (x+1)^{n/2} \times P^{(1)}(x+1)$
- 2 evaluate  $P^{(0)}(x+1)$  and  $P^{(1)}(x+1)$  recursively
- 3 compute a product when  $P^{(1)}(x+1)$  is evaluated
- **o** compute a sum when  $P^{(0)}(x+1)$  and the product are evaluated

These are the four main things to implement to realize the *Taylor shift by* 1. We will only focus on the multiplication, which is the most hard and tricky operation to realize our code.

Intership context

- Small sizes  $(n \le 512)$ :
  - We can use a procedure called *list\_Plain\_Mul* which computes a list of pairwise products of polynomials of same size.
- Big sizes (n > 512):

We can use *FFT* whic several procedures which compute a list pairwise products of polynomials of <u>same size</u>.

Polynomials considered at step i: Polynomials  $P^{(1)}$  (of size  $2^i$ ) and  $(x+1)^{2^i}$  (of size  $2^i+1$ ).

# Multiplication: a challenge

#### Problems:

- Polynomials considered <u>must be of the same size</u> (rather  $2^i$ ) so as to use the procedures of the lab.
- Size of the product of two such polynomials is not a power of 2 (but  $2^{i+1} 1$ ).

#### Solutions:

- Modify procedure list Plain Mul and adapt it for my case.
- Consider another product with polynomials of same sizes.

Intership context

# Multiplication: decomposition

We can decompose the product desired as follows:

$$P^{(1)}(X) \times (X+1)^{2^{i}} = \left(\sum_{i=0}^{2^{i}-1} a_{i} X^{i}\right) \times (X+1)^{2^{i}}$$

$$= P^{(1)}(X) \times \left[(X+1)^{2^{i}} - 1 + 1\right]$$

$$= P^{(1)}(X) \times \left[(X+1)^{2^{i}} - 1\right] + P^{(1)}(X)$$

$$= P^{(1)}(X) \times X \times \frac{(X+1)^{2^{i}} - 1}{X} + P^{(1)}(X)$$

$$= X \cdot \left(P^{(1)}(X) \times \frac{(X+1)^{2^{i}} - 1}{X}\right) + P^{(1)}(X)$$

## Taylor shift multiplication concept

Using the following formula:

Intership context

$$P^{(1)}(X) \times (X+1)^{2^i} = X \cdot \left(P^{(1)}(X) \times \frac{(X+1)^{2^i}-1}{X}\right) + P^{(1)}(X)$$

The multiplication desired amounts to :

- multiplying  $P^{(1)}(X)$  by  $[(X+1)^{2^{i}}-1]/X$  of sizes  $2^{i}$ ,
- 2 doing a right shift (multiplication by X), and
- 3 semi-adding the result of the two first steps with  $P^{(1)}(X)$ .

We will just detail how to do the multiplication for the two cases of polynomial sizes.

# Multiplication: arrays considered (artificial ex.)

If we consider polynomials at step 1:

Then for the two multiplication techniques used, we consider:

- "Small sizes"  $(n \le 512)$ :
  - Mgpu = 3
- "Big sizes" (n > 512):
  - fft device = 3

# Multiplication according to the size of the polynomials

### • "Small sizes" $(n \le 512)$ :

We use Mgpu and multiply directly pairwise polynomials inside, then do a right shift. Product size is still a power of 2. So  $list\_Plain\_Mul\_and\_right\_shift$  is used to do :  $X \cdot \left(P^{(1)}(X) \times [(X+1)^{2^i}-1]/X\right)$ .

#### • "Big sizes" (n > 512):

We transform Mgpu in  $fft\_device$  and then use FFT for the multiplication  $P^{(1)}(X) \times [(X+1)^{2^i}-1]/X$ .

The FFT will be explained in the following section.

### First definition

#### Definition

Let *n* be a positive integer and  $\omega \in R$ .

- $\omega$  is a *n*-th root of unity if  $\omega^n = 1$ .
- $\omega$  is a primitive *n*-th root of unity if :
  - (1)  $\omega^n = 1$ .
  - (2)  $\omega$  is a unit in R.
  - (3)  $\forall t$  prime s.t.  $t|n, \omega^{n/t} 1$  is neither 0 nor a 0 divisor.

We now take  $\omega \in R$  to be a primitive *n*-th root of unity.

# Discrete Fourier transform (DFT)

#### Definition

The R-linear map

$$DFT_{\omega}: egin{cases} R^n & 
ightarrow R^n \ f & \mapsto (f(1),f(\omega),f(\omega^2),\ldots,f(\omega^{n-1})) \end{cases}$$

which evaluates a polynomial at the powers of  $\omega$  is called the **Discrete** Fourier Transform (DFT).

## Proposition (consequence of the Lagrange's theorem)

The R-linear map  $DFT_{\omega}$  is an isomorphism.

Then we can represent a polynomial f by the DFT representation with  $\omega$  determined in our code.

### Convolution

#### **Definition**

Intership context

The convolution w.r.t. n of  $f = \sum_{0 \le i < n} f_i x^i$  and  $g = \sum_{0 \le i < n} g_i x^i$  in R[x] is  $h = f * g = \sum_{0 \le k < n} h_k x^k$  s.t.

$$\forall k \in \llbracket 0, n-1 \rrbracket, \ h_k = \sum_{i+j \equiv k \mod n} f_i \, g_j$$

One can prove that  $fg = f * g \mod (x^n - 1)$ .

## Lemma (DFT product amounts to a scalar product)

For  $f,g\in R[x]$  univariate polynomials of degree less than n we have

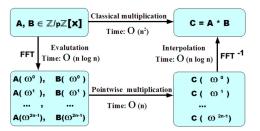
$$DFT_{\omega}(f * g) = DFT_{\omega}(f)DFT_{\omega}(g).$$

## FFT Maping

#### Definition

The Fast Fourier Transform (FFT) is an efficient algorithm to compute *DFT* and its inverse.

We use the Cooley-Tukey algorithm following a D&C strategy.



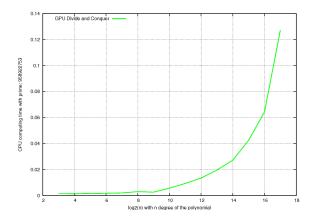
FFT-based univariate polynomial multiplication over  $\mathbb{Z}/p\mathbb{Z}$ 

## Taylor shift by 1 execution times

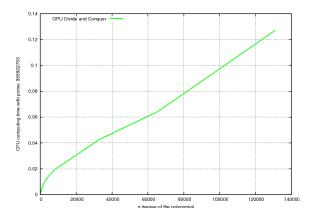
#### Results are for polynomials of sizes $n = 2^e$ :

Execution time in seconds									
е	n	GPU	CPU : HOR	CPU : DNC	Maple 16				
3	8	0.001518	0.000128	0.000141	<0.001				
4	16	0.001432	0.000186	0.000172	< 0.001				
5	32	0.001590	0.000167	0.000191	<0.001				
6	64	0.001773	0.000192	0.000294	0.008				
7	128	0.002016	0.000261	0.000628	0.024				
8	256	0.003036	0.000593	0.002331	0.084				
9	512	0.002624	0.001278	0.006304	0.320				
10	1024	0.005756	0.005940	0.032073	1.400				
11	2048	0.009317	0.015312	0.095027	5.640				
12	4096	0.013475	0.076866	0.376543	24.478				
13	8192	0.019674	0.324029	1.498890	104.438				
14	16384	0.027229	1.282708	6.861433	437.848				
15	32768	0.042561	5.110919	23.907799	1781.427				
16	65536	0.064306	15.184347	114.988129	7407.063				
17	131072	0.127214	80.625801	477.934692	>10000				

#### Execution time of the GPU in function of e

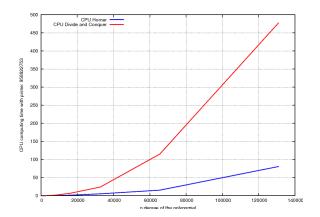


#### Execution time of the GPU in function of n

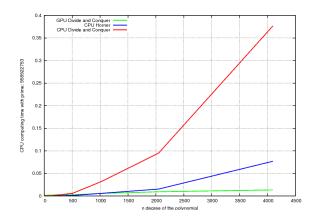


This execution time is approximatively linear.

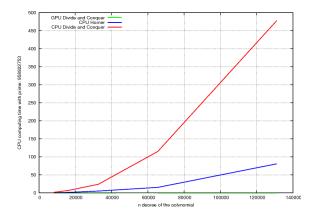
## Execution times of the CPU in function of *n*



# Execution times in function of n for small degrees



## Execution times in function of n for big degrees



We clearly improve performances using GPUs.

Remark: the behaviour of the CPU times is the same for the different sizes.

## Possible improvements & FFT primes

- We need to improve the parallel computation of the sequence  $(i!)_{1 \le i \le n}$ , and
- We can reduce the size of the array storing the elements of  $(x+1)^{2^i}$  as these polynomials are symmetric.

The *Taylor shift* modulo p is needed several times to get the *Taylor shift* in  $\mathbb{Z}$ . Two questions arises :

• What prime numbers must we use?

Intership context

2 How many such primes numbers must we use?

Primes numbers of the form  $p = M \times 2^j + 1$  yield the best performance for *FFT*, with p > n and  $M < 2^j$  odd integer.

Intership context

## Combination with the Chinese Remainder thm.

We need to Taylor shift by a prime number  $(m_i)_{1 \le i \le s}$  s times. For each coefficient in  $\mathbb{Z}$ , we obtain a vector  $\mathbf{x} = (x_1, \dots, x_s)$ .

**Objective**: using the *CRT2*, compute the image a of x by  $\mathbb{Z}/m_1\mathbb{Z}\times\cdots\times\mathbb{Z}/m_s\mathbb{Z}\cong\mathbb{Z}/m_1\cdots m_s\mathbb{Z}$ .

**Representation**: we can represent a by  $\mathbf{b} = (b_1, \dots, b_s)$  s.t.  $\mathbf{a} = b_1 + b_2 m_2 + b_3 m_1 m_2 + \dots + b_s m_1 \dots m_{s-1}$ .

Then we will use the conversion of modular numbers to their mixed radix representation by a matrix formula to compute **b**.

# Definition (1)

Intership context

Let us consider  $m_1, m_2, \ldots, m_s$  distinct prime numbers.

Definition 
$$((m_{i,j})$$
 and  $(n_{i,j}))$ 

We define the sequences  $(m_{i,j})_{1 \le i \le j \le s}$  and  $(n_{i,j})_{1 \le i \le j \le s}$  such that :

$$\begin{cases} m_{i,j} \times m_i \equiv 1 \mod m_j \mid 0 \le m_{i,j} < m_j \\ n_{i,j} = m_j - m_{i,j} \end{cases}$$

Benchmarks

# Definition (2)

### Definition (matrix A)

We define the matrix  $(A_k)_{1 \le k \le s-1}$  as the following :

$$A_k = \left(\begin{array}{c|c} I_{k-1} & 0 \\ \hline 0 & B_k \end{array}\right) \text{ with }$$

$$B_{k} = \begin{pmatrix} 1 & n_{k,k+1} & n_{k,k+2} & \dots & n_{k,s} \\ 0 & m_{k,k+1} & 0 & \dots & 0 \\ \vdots & \ddots & m_{k,k+2} & \ddots & \vdots \\ \vdots & & \ddots & \ddots & 0 \\ 0 & \dots & \dots & 0 & m_{k,s} \end{pmatrix}$$

# Mixed radix representation by a matrix formula

#### **Theorem**

Intership context

$$b = (...(((xA_1)A_2)A_3)...) A_{s-1}$$

#### Definition

As  $A_k$  is sparse, we don't really need to multiply our results by a matrix. Thus, we will consider sequences  $(L_k)_{1 \le k \le s-1}$  and  $(D_k)_{1 \le k \le s-1}$ respectively the first row of  $A_k$  and the diagonal of  $A_k$  such that :

$$(L_k) = (n_{k,j} | k+1 \le j \le s),$$

$$(D_k) = (m_{k,j} \mid k+1 \le j \le s).$$

This gives the following algorithm (with  $d = n - 1 = 2^e - 1$ ):

Intership context

## Algorithm for the mixed radix representation

```
Input : X[0..d][1..s], s, (m_i)_{1 \le i \le s}, (L_k)_{1 \le k \le s-1}, (D_k)_{1 \le k \le s-1}
\mathbf{Y} \cdot = \mathbf{X}
for k = 1..s - 1 do
   for i = 0 d do
       for i = k + 1..s do
           Y_{i,i} := \left[ \left( Y_{i,i} L_{k,i} \mod m_i \right) + \left( Y_{i,j} D_{k,j} \mod m_i \right) \right]
       end do
   end do
end do
Output : Y[0..d][1..s]
```

This algorithm can be parallelized but the different loops in k need less and less computations, parallelization must me done with reflection.