

Dynamics of Selmer's continued fraction algorithm

Henk Bruin

University of Vienna (Austria)

Joint with

Robbert Fokkink & Cor Kraaikamp

TU Delft (Netherlands)

May 2013

The Euclidean Algorithm

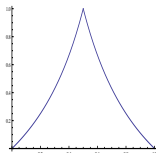
An example from very old Greeks:

Let $x < y$ be positive real numbers.

The Euclidean algorithm to approximate $\frac{x}{y}$ by rationals goes by iterating:

$$(x, y) \rightarrow \begin{cases} (x, y - x) & \text{if } x < y - x, \\ (y - x, x) & \text{if } x > y - x. \end{cases}$$

If we scale the largest coordinate to 1, we get the Farey map:



$$f(x) = \begin{cases} \frac{x}{1-x} & \text{if } x < \frac{1}{2}, \\ \frac{1-x}{x} & \text{if } x > \frac{1}{2}. \end{cases}$$

The Gauß map

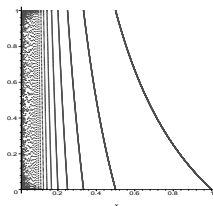
To speed up this algorithm, define

$$\tau(x) = 1 + \min\{n \geq 0 : f^n(x) \in (\frac{1}{2}, 1]\}.$$

The induced map $G = f^\tau$ is the **Gauß map**: $G(x) = \frac{1}{x} - \lfloor \frac{1}{x} \rfloor$

It produces the standard continued fraction of x by $x_n = G^n(x)$, $a_{n+1} = \lfloor \frac{1}{x_n} \rfloor$:

$$x = \frac{1}{a_1 + \frac{1}{a_2 + \frac{1}{a_3 + \frac{1}{\ddots}}}}$$



The Gauß map

The Gauß map G preserves the measure

$$d\nu = \frac{1}{\log 2} \frac{1}{1+x} dx,$$

which allows us to make statistical prediction of the continued fraction digits a_n of Lebesgue typical x .

The Gauß map

The Gauß map G preserves the measure

$$d\nu = \frac{1}{\log 2} \frac{1}{1+x} dx,$$

which allows us to make statistical prediction of the continued fraction digits a_n of Lebesgue typical x .

However ν does **not** pull back to an f -invariant **probability** measure.

Instead, the Farey map preserves the infinite density

$$d\mu = \frac{1}{x} dx$$

The Lebesgue statistical properties of the Farey map are nevertheless very well understood, e.g. Thaler.

Algorithms in higher dimension.

Let $\vec{x} = (x_1, \dots, x_d)$ be a d -tuple of positive reals. and π a permutation on $\{1, \dots, d\}$.

Any subtractive algorithm can be composed of basic maps

$$T_\pi(\vec{x}) = \pi \circ (x_1, \dots, x_{d-1}, x_d - x_1)$$

and then iterated

$$T^n(\vec{x}) = T_{\pi_n} \circ T_{\pi_{n-1}} \circ \dots \circ T_{\pi_1},$$

where the permutations may depend on the argument \vec{x} , (for example, to sort in increasing order).

Algorithms in higher dimension.

$$T^n(\vec{x}) = T_{\pi_n} \circ T_{\pi_{n-1}} \circ \cdots \circ T_{\pi_1},$$

You can scale to unit size (say $\max x_j = 1$) at any moment:

$$f^n(\vec{x}) = \frac{1}{\max \hat{x}_j} \hat{x} \quad \text{for } \hat{x} = T^n(\vec{x}).$$

Thus f acts on

$$\Delta_d = \{\vec{x} = (x_1, \dots, x_{d-1}) : 0 \leq x_i \leq 1\}.$$

NB: The boundary $x_1 \equiv 0$ of Δ_d consists of **neutral fixed points**.

Selmer's Algorithm and Selmer's Generalised Algorithm

Let $a \in \mathbb{N}$ and define:

$$T(\vec{x}) = \text{sort}(x_1, \dots, x_a, x_{a+1} - x_1)$$

Here sort means: rearrange in increasing order.

Selmer's Algorithm and Selmer's Generalised Algorithm

Let $a \in \mathbb{N}$ and define:

$$T(\vec{x}) = \text{sort}(x_1, \dots, x_a, x_{a+1} - x_1)$$

Here sort means: rearrange in increasing order.

Generalise as follows: Let $a, b \in \mathbb{N}$, $d = a + b$.

$$T(\vec{x}) = \text{sort}(x_1, \dots, x_a, x_{a+1} - x_1, \dots, x_d - x_1).$$

Selmer's Algorithm and Selmer's Generalised Algorithm

Let $a \in \mathbb{N}$ and define:

$$T(\vec{x}) = \text{sort}(x_1, \dots, x_a, x_{a+1} - x_1)$$

Here sort means: rearrange in increasing order.

Generalise as follows: Let $a, b \in \mathbb{N}$, $d = a + b$.

$$T(\vec{x}) = \text{sort}(x_1, \dots, x_a, x_{a+1} - x_1, \dots, x_d - x_1).$$

Question 1: Is $\lim_{n \rightarrow \infty} T^n(\vec{x}) = \vec{0}$?

Selmer's Algorithm and Selmer's Generalised Algorithm

Let $a \in \mathbb{N}$ and define:

$$T(\vec{x}) = \text{sort}(x_1, \dots, x_a, x_{a+1} - x_1)$$

Here `sort` means: rearrange in increasing order.

Generalise as follows: Let $a, b \in \mathbb{N}$, $d = a + b$.

$$T(\vec{x}) = \text{sort}(x_1, \dots, x_a, x_{a+1} - x_1, \dots, x_d - x_1).$$

Question 1: Is $\lim_{n \rightarrow \infty} T^n(\vec{x}) = \vec{0}$?

That means: **typically**. If there are rational relations between the coordinates, e.g. $x_{a+1} = x_1$, then x_1 can become zero in finitely many steps, and \vec{x} won't change anymore.

Trapping regions

Rephrase **Question 1**: Is $\vec{x}^\infty := \lim_{n \rightarrow \infty} T^n(\vec{x}) = \vec{0}$?

Trapping regions

Rephrase **Question 1**: Is $\vec{x}^\infty := \lim_{n \rightarrow \infty} T^n(\vec{x}) = \vec{0}$?

For the case $a = 1, b = 2$, *i.e.*,

$$T(x_1, \dots, x_3) = \text{sort}(x_1, x_2 - x_1, x_3 - x_1),$$

the quantity $\eta := x_3 - x_2 - x_1$ is preserved, as soon as it is positive.

Trapping regions

Rephrase **Question 1**: Is $\vec{x}^\infty := \lim_{n \rightarrow \infty} T^n(\vec{x}) = \vec{0}$?

For the case $a = 1, b = 2$, *i.e.*,

$$T(x_1, \dots, x_3) = \text{sort}(x_1, x_2 - x_1, x_3 - x_1),$$

the quantity $\eta := x_3 - x_2 - x_1$ is preserved, as soon as it is positive.

Therefore, if at some iterate $\eta > 0$, then $x_3^\infty = \eta > 0$.

In particular, Lebesgue measure is **not** ergodic.

We call $\{\vec{x} \in \mathbb{R}_+^3 : x_1 + x_2 < x_3\}$ the **trapping region**.

Trapping Regions

Answer to **Question 1**: Is $\lim_{n \rightarrow \infty} T^n(\vec{x}) = \vec{0}$?

Trapping Regions

Answer to **Question 1**: Is $\lim_{n \rightarrow \infty} T^n(\vec{x}) = \vec{0}$?

For Selmer's Generalised Algorithm we have the following answer:

Trapping Theorem The r -th coordinate of $\vec{x}^\infty := \lim_{n \rightarrow \infty} T^n(\vec{x})$ is zero

$$\left\{ \begin{array}{ll} \text{almost surely} & \text{if } r \leq a + 1, \\ \text{with probability strictly} & \text{if } a + 1 < r \\ \text{between 0 and 1} & \leq \min\{a + b, 2a\}. \end{array} \right.$$

Trapping Regions

Answer to **Question 1**: Is $\lim_{n \rightarrow \infty} T^n(\vec{x}) = \vec{0}$?

For Selmer's Generalised Algorithm we have the following answer:

Trapping Theorem The r -th coordinate of $\vec{x}^\infty := \lim_{n \rightarrow \infty} T^n(\vec{x})$ is zero

$$\left\{ \begin{array}{ll} \text{almost surely} & \text{if } r \leq a + 1, \\ \text{with probability strictly} & \text{if } a + 1 < r \\ \text{between 0 and 1} & \leq \min\{a + b, 2a\}. \end{array} \right.$$

For $r > 2a$ there is **no Markov partition**. Numerical experiments suggest that the r -th coordinate is positive for Lebesgue-a.e. \vec{x} .

Trapping regions

Recall Selmer's generalised algorithm

$$\begin{cases} T(\vec{x}) = \text{sort}(x_1, \dots, x_a, x_{a+1} - x_1, \dots, x_d - x_1), \\ f(\vec{x}) = \frac{1}{\hat{x}_d} \vec{x} \quad \hat{x} = T(\vec{x}). \end{cases}$$

for $a, b \in \mathbb{N}$, $d = a + b$.

The r -th **Trapping Region** is

$$\mathcal{T}_r = \left\{ \vec{x} \in \Delta_d : \frac{1}{r-a} \sum_{j \leq r} x_j < x_r \right\}.$$

If $\vec{x} \in \mathcal{T}_r$, then x_1, \dots, x_{r-1} combined are too small to pull x_r to zero.

Rational Approximations

The map T is piecewise linear; each iterate T^k is given by an integer matrix A_k that depends on \vec{x} . Its inverse

$$A_k^{-1} = \begin{pmatrix} p_{1,k} & p_{1,k-1} & \cdots & \cdots & p_{1,k-d+1} \\ \vdots & \vdots & & & \vdots \\ \vdots & \vdots & & & \vdots \\ p_{d-1,k} & p_{d-1,k-1} & \cdots & \cdots & p_{d-1,k-d+1} \\ q_k & q_{k-1} & \cdots & \cdots & q_{k-d+1} \end{pmatrix}.$$

is also integer and has non-negative entries.

In projective space, the columns of A_k^{-1} approximate \vec{x} , **provided**
 $T^k(\vec{x}) \rightarrow \vec{0}$.

Rational Approximations

Hence,

$$\left(\frac{p_{1,k-j}}{q_{k-j}}, \dots, \frac{p_{d-1,k-j}}{q_{k-j}} \right) \quad \text{for each } 0 \leq j < d,$$

are rational approximations of $\left(\frac{x_1}{x_d}, \dots, \frac{x_{d-1}}{x_d} \right)$

Rational Approximations

Hence,

$$\left(\frac{p_{1,k-j}}{q_{k-j}}, \dots, \frac{p_{d-1,k-j}}{q_{k-j}} \right) \quad \text{for each } 0 \leq j < d,$$

are rational approximations of $\left(\frac{x_1}{x_d}, \dots, \frac{x_{d-1}}{x_d} \right)$

To see this: Each column of A_k^{-1} is orthogonal to all rows of A_k , except one. Each column therefore spans the orthogonal complement of $d - 1$ rows. If $\lim_{k \rightarrow \infty} A_k \vec{x} = \vec{0}$, then \vec{x} is nearly orthogonal to all rows of A_k .

Rational Approximations

Hence,

$$\left(\frac{p_{1,k-j}}{q_{k-j}}, \dots, \frac{p_{d-1,k-j}}{q_{k-j}} \right) \quad \text{for each } 0 \leq j < d,$$

are rational approximations of $\left(\frac{x_1}{x_d}, \dots, \frac{x_{d-1}}{x_d} \right)$

To see this: Each column of A_k^{-1} is orthogonal to all rows of A_k , except one. Each column therefore spans the orthogonal complement of $d - 1$ rows. If $\lim_{k \rightarrow \infty} A_k \vec{x} = \vec{0}$, then \vec{x} is nearly orthogonal to all rows of A_k .

Therefore, in projective space, \vec{x} is close to the column vectors of A_k^{-1} . The quality of the approximation depends on the rate of convergence of $T^k(\vec{x}) \rightarrow \vec{0}$; if $\lim_k T^k(\vec{x}) \neq \vec{0}$, then T gives no approximations at all.

Quality of Approximations

Dirichlet's Theorem states that every vector \vec{x} has infinitely many rational approximations \vec{w} of denominator $q = q(\vec{w})$ such that

$$\|\vec{w} - \vec{x}\| \leq q^{-(1+1/(d-1))}. \quad (1)$$

(NB: The norm is taken after dividing by the largest coordinate!)

Quality of Approximations

Dirichlet's Theorem states that every vector \vec{x} has infinitely many rational approximations \vec{w} of denominator $q = q(\vec{w})$ such that

$$\|\vec{w} - \vec{x}\| \leq q^{-(1+1/(d-1))}. \quad (1)$$

(NB: The norm is taken after dividing by the largest coordinate!)

The standard continued fraction algorithm in dimension $d - 1 = 1$ achieves this: It finds the best approximants, with $|w - x| \leq q^{-2}$.

Quality of Approximations

Dirichlet's Theorem states that every vector \vec{x} has infinitely many rational approximations \vec{w} of denominator $q = q(\vec{w})$ such that

$$\|\vec{w} - \vec{x}\| \leq q^{-(1+1/(d-1))}. \quad (1)$$

(NB: The norm is taken after dividing by the largest coordinate!)

The standard continued fraction algorithm in dimension $d - 1 = 1$ achieves this: It finds the best approximants, with $|w - x| \leq q^{-2}$.

In higher dimension, there is no known subtractive algorithm that finds all best approximants, or even achieves infinitely many approximants satisfying (1).

Quality of Approximations

Following Lagarias '93, let

$$\eta(\vec{w}, \vec{x}) = \frac{-\log \|\vec{w} - \vec{x}\|}{\log q}$$

Quality of Approximations

Following Lagarias '93, let

$$\eta(\vec{w}, \vec{x}) = \frac{-\log \|\vec{w} - \vec{x}\|}{\log q}$$

The **best approximation exponent** is

$$\eta(\vec{x}) = \limsup_{k \rightarrow \infty} \sup_{0 \leq i < d} \eta(\vec{w}_{k,i}, \vec{x})$$

The **uniform approximation exponent** is

$$\eta^*(\vec{x}) = \inf_k \frac{\min_{0 \leq i < d} -\log \|\vec{w}_{k,i} - \vec{x}\|}{\max_{0 \leq i < d} \log q_{k-i}}.$$

Quality of Approximations

These are chosen such that we can conclude

$$\|\vec{w}_{k,i} - \vec{x}\| \leq \begin{cases} q_{k-i}^{-\eta(\vec{x})} & \text{infinitely often} \\ q_{k-i}^{-\eta^*(\vec{x})} & \text{for all } k, i. \end{cases}$$

Quality of Approximations

These are chosen such that we can conclude

$$\|\vec{w}_{k,i} - \vec{x}\| \leq \begin{cases} q_{k-i}^{-\eta(\vec{x})} & \text{infinitely often} \\ q_{k-i}^{-\eta^*(\vec{x})} & \text{for all } k, i. \end{cases}$$

Thus Dirichlet's Theorem states that

$$\eta(\vec{x}) \geq 1 + 1/(d - 1)$$

for every \vec{x} , provided the algorithm finds infinitely many of the best approximations.

Quality of Approximations

Main Theorem: For Selmer's Generalised Algorithm with $a \geq \max\{2, b\}$, Lebesgue-a.e. vector $\vec{x} \in \mathcal{V}_d$ satisfies

$$\eta(\vec{x}) = \eta^*(\vec{x}) = 1 - \frac{\lambda_2}{\lambda_1} > 1,$$

where $\lambda_1 > 0 > \lambda_2$ are the largest two typical Lyapunov exponents of the cocycle A_k^{-1} .

Quality of Approximations

Main Theorem: For Selmer's Generalised Algorithm with $a \geq \max\{2, b\}$, Lebesgue-a.e. vector $\vec{x} \in \mathcal{V}_d$ satisfies

$$\eta(\vec{x}) = \eta^*(\vec{x}) = 1 - \frac{\lambda_2}{\lambda_1} > 1,$$

where $\lambda_1 > 0 > \lambda_2$ are the largest two typical Lyapunov exponents of the cocycle A_k^{-1} .

Remark: If all negative Lyapunov exponents are equal, then

$$1 - \frac{\lambda_2}{\lambda_1} = 1 + 1/(d - 1).$$

Finding an algorithm with this equality of Lyapunov exponents is extremely unlikely.

Quality of Approximations

Remarks on the Proof:

The Main Theorem follows from the work of Lagarias '93, based on Oseledec' Theorem on Lyapunov exponents of matrix-valued cocycles (here A_k^{-1}).

We need:

Quality of Approximations

Remarks on the Proof:

The Main Theorem follows from the work of Lagarias '93, based on Oseledec' Theorem on Lyapunov exponents of matrix-valued cocycles (here A_k^{-1}).

We need:

- ▶ an invariant measure μ (despite the neutral fixed points, a finite μ exists when $a \geq \max\{2, b\}$);

Quality of Approximations

Remarks on the Proof:

The Main Theorem follows from the work of Lagarias '93, based on Oseledec' Theorem on Lyapunov exponents of matrix-valued cocycles (here A_k^{-1}).

We need:

- ▶ an invariant measure μ (despite the neutral fixed points, a finite μ exists when $a \geq \max\{2, b\}$);
- ▶ **positive acceleration**: consider f^R so that A_R^{-1} is strictly positive (can be done μ -a.e.);

Quality of Approximations

Remarks on the Proof:

The Main Theorem follows from the work of Lagarias '93, based on Oseledec' Theorem on Lyapunov exponents of matrix-valued cocycles (here A_k^{-1}).

We need:

- ▶ an invariant measure μ (despite the neutral fixed points, a finite μ exists when $a \geq \max\{2, b\}$);
- ▶ **positive acceleration**: consider f^R so that A_R^{-1} is strictly positive (can be done μ -a.e.);
- ▶ tail estimates on R ;

Quality of Approximations

Remarks on the Proof:

The Main Theorem follows from the work of Lagarias '93, based on Oseledec' Theorem on Lyapunov exponents of matrix-valued cocycles (here A_k^{-1}).

We need:

- ▶ an invariant measure μ (despite the neutral fixed points, a finite μ exists when $a \geq \max\{2, b\}$);
- ▶ **positive acceleration**: consider f^R so that A_R^{-1} is strictly positive (can be done μ -a.e.);
- ▶ tail estimates on R ;
- ▶ **Challenge**: Estimate λ_1 and λ_2 ;

Quality of Approximations

Remarks on the Proof:

The Main Theorem follows from the work of Lagarias '93, based on Oseledec' Theorem on Lyapunov exponents of matrix-valued cocycles (here A_k^{-1}).

We need:

- ▶ an invariant measure μ (despite the neutral fixed points, a finite μ exists when $a \geq \max\{2, b\}$);
- ▶ **positive acceleration**: consider f^R so that A_R^{-1} is strictly positive (can be done μ -a.e.);
- ▶ tail estimates on R ;

- ▶ **Challenge**: Estimate λ_1 and λ_2 ;
- ▶ **Challenge**: What about non-typical \vec{x} ?

References

- ▶ H. Bruin, R. Fokkink, C. Kraaikamp, *The convergence of the generalised Selmer algorithm*, Preprint 2013
- ▶ V. Brun, *Musikk og euklidiske algoritmer*, Nord. Mat. Tidskr. **9** (1961), 29–36.
- ▶ R. Fokkink, C. Kraaikamp, H. Nakada, *On Schweiger's conjectures on fully subtractive algorithms*, Israel J. Math. **186** (2011), 285–296.
- ▶ J. C. Lagarias, *The quality of the Diophantine approximations found by the Jacobi-Perron algorithm and related algorithms*, Monatsh. Math. **115** (1993), 299–328.
- ▶ E. S. Selmer, *Om Flerdimensjonaler Kjedebrøk*, Nord. Mat. Tidskr. **9** (1961), 37–43.
- ▶ M. Thaler, *Transformations on $[0, 1]$ with infinite invariant measures*, Israel J. Math. **46** (1983), 67–96.