

On the complexity of finding shortest linear recurrences.

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Abstract

The Berlekamp-Massey Algorithm finds shortest linear-feedback shift register which generates a given sequence over a finite field. We show that it requires at most $2\lfloor n^2/4 \rfloor - n + 1$ multiplications for a sequence of length n . This improves a result of Gustavson by $\lfloor (3n-1)/2 \rfloor$.

A shortest linear recurrence can be obtained using Algorithm MR, due to the author. This algorithm is algebraic and independent of any particular application. We derive a monic version of it and show that at most $2\lfloor n^2/4 \rfloor - n$ multiplications are required. However since the monic Algorithm MR has a simpler control structure and admits parallelism, it is a practical improvement on the Berlekamp-Massey Algorithm.

Both analyses follow directly from a tight upper bound on the sum of the linear complexities of a sequence of length n : $\sum_{i=1}^{n-1} L_i \leq \lfloor n^2/4 \rfloor$, which may be of independent interest.

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1 Introduction

1.1 The Berlekamp-Massey Algorithm

Applications of finding a shortest linear recurrence or linear-feedback shift register (LFSR) via the Berlekamp-Massey (or LFSR synthesis) Algorithm [5, p. 124] are manifold in Coding Theory, Cryptography, Mathematical Systems Theory and Algebraic Computation. For a survey, see [9, Introduction]. We begin by discussing the worst-case complexity of this algorithm.

Recall that for $n \geq 1$, the linear complexity L_n of a finite sequence (S_0, \dots, S_{n-1}) over a field is the least non-negative integer such that (S_0, \dots, S_{n-1}) are the first n terms of an order L_n linear recurrence (or the first n outputs of an LFSR of shortest length L_n , [5]); by convention, $L_0 = 0$. Our analysis is based on an algorithm-free lemma that $\sum_{i=1}^{n-1} L_i \leq B_n \stackrel{\text{defn}}{=} \lfloor n^2/4 \rfloor$. Here the sequence is over any domain. Our inequality is tight and may be of independent interest. We note that in [2, Proof of Lemma 2.1], it was claimed that $\sum_{i=1}^{2t-1} L_i \leq t^2$.

We deduce that the Berlekamp-Massey algorithm requires at most $2B_n - n + 1$ multiplications for a sequence of length n . Our result improves the bound $n(n + 1)/2$ of [4] (which was claimed to be tight) by $\lfloor (3n - 1)/2 \rfloor$. Some additional remarks concerning [4] appear in the Appendix. We include an elementary inductive proof of the distribution of fixed-length sequences of prescribed linear complexity over a finite field, proved in [4] using the Berlekamp-Massey Algorithm.

1.2 Algorithm MR

Next we discuss the worst-case complexity of finding a shortest linear recurrence via Algorithm MR of [7, 9], where we developed a theory of shortest linear recurrences for finite sequences over a commutative integral domain R from first principles. (We viewed linear recurring sequences as torsion elements in the standard $R[X]$ -module of Laurent series in X^{-1} , $R((X^{-1}))$); a shortest linear recurrence of the sequence then corresponds to a generator of its annihilator ideal in $R[X]$. The standard $R[X]$ -module of Laurent *polynomials* $R[X^{-1}, X]$ then formed the basis of our approach to *finite* sequences. Thus our algebraic approach is independent of LFRS's and any particular application.)

The linear complexity L_n is now the degree of any non-zero 'minimal polynomial' $\mu \in R[X]$ of the given finite sequence (and we no longer require the convention $L_0 = 0$). For a precise statement of the equivalence of shortest LFRS's and minimal polynomials, see [9, Proposition 2.1, Corollary 2.3]. Algorithm MR actually computes a 'minimal realization' $(\mu, \beta) \in R[X] \times XR[X]$ of the sequence; the original sequence coincides with the initial coefficients of $\beta/\mu \in R[[X^{-1}]]$ when μ is monic.

We summarise the theory underlying Algorithm MR in Section 3.2; a simple counting argument ([7, Proposition 3.23]) showed that it is $\mathcal{O}(n^2)$. However, using our linear complexity bound, we deduce that Algorithm MR computes a minimal polynomial in at most $3B_n + 2n - 7$ R -multiplications, Proposition 3.5.

When $R = \mathbb{F}$ is a field, we derive a version of Algorithm MR which computes a *monic* minimal polynomial at each iteration, in such a way that the multiplications always involve the polynomials of smaller degree. This monic algorithm requires at most $2B_n - n$ multiplications.

We also show that computing β requires at most $B_n - n + 1$ more \mathbb{F} -multiplications. We remark that β could also be obtained by simply multiplying μ and the 'generating function' of the sequence in $\mathbb{F}[X^{-1}, X]$, for at most $n \deg(\mu) \leq n^2 \sim 2B_n$ multiplications. However, from a circuitry viewpoint, Algorithm MR computes β using the same control logic as for μ , differing only in the initialization. Thus μ and β could be computed in parallel, and so using Algorithm MR to compute β (without additional $\mathbb{F}[X^{-1}, X]$ -multiplication circuitry) seems preferable.

1.3 Conclusions

Compared to the Berlekamp-Massey Algorithm, Algorithm MR has a simpler derivation, it is structured, valid over any integral domain, admits parallelism and generalizes readily to finite chain rings, [8] and to multiple sequences, [10].

We have shown that the monic Algorithm MR and the Berlekamp-Massey Algorithm have virtually identical worst-case complexity. Algorithm MR also has storage and logic-circuit advantages over the Berlekamp-Massey Algorithm. Thus we have made both conceptual and implementation gains by being mathematical rather than application-oriented, with no loss in run-time efficiency.

Average-case analyses of Algorithm MR for sequences of integers (perhaps adapting the techniques of [3]) and of the monic Algorithm MR for sequences over a finite field would be interesting.

2 The linear complexity bound B_n

Linear complexity is usually computed algorithmically, but to emphasize that our bound is independent of any particular algorithm, we use the following definition suggested by [5, Theorem 2]:

DEFINITION 2.1 *Let D be a domain and $d_1, \dots, d_{n-1} \in D$. Put $L_{-1} = L_0 = 0$. For $0 \leq i \leq n-2$ we inductively define $L_{i+1} \in \{0, 1, 2, \dots\}$ by*

$$L_{i+1} = \begin{cases} L_i & \text{if } d_{i+1} = 0 \\ \max\{L_i, i+1 - L_i\} & \text{if } d_{i+1} \neq 0. \end{cases}$$

Now $\sum_{i=1}^{n-1} L_i \leq \lfloor n^2/4 \rfloor$ is trivially satisfied if $L_i \leq \lfloor (i+1)/2 \rfloor$ for $0 \leq i \leq n-1$ since it is easy to check that $\sum_{i=1}^{n-1} \lfloor (i+1)/2 \rfloor = \lfloor n^2/4 \rfloor$. However, $L_i \leq \lfloor (i+1)/2 \rfloor$ does not hold in general: consider a sequence of length $n \geq 2$ which is zero except for its last term for example.

On the other hand, if (S_0, \dots, S_{n-1}) is such that d_1, \dots, d_{n-1} are non-zero, then $L_i = \lfloor (i+1)/2 \rfloor$ for $0 \leq i \leq n-1$, so $\sum_{i=1}^{n-1} L_i = \lfloor n^2/4 \rfloor$ in this case.

LEMMA 2.2 *We have $\sum_{i=1}^{n-1} L_i \leq B_n$, where $B_n \stackrel{\text{defn}}{=} \lfloor n^2/4 \rfloor$.*

PROOF. It is enough to show that

$$\sum_{j=1}^{n-1} L_j \leq \sum_{j=1}^{n-1} \lfloor (j+1)/2 \rfloor. \quad (1)$$

It is convenient to call j *stable* if it is odd, $L_j = \lfloor (j+1)/2 \rfloor$ and $\sum_{i=1}^j L_i \leq \sum_{i=1}^j \lfloor (i+1)/2 \rfloor$. Clearly -1 is stable, so suppose inductively that $s \stackrel{\text{defn}}{=} 2u - 1 \geq -1$ is stable, so that $L_s = u$. Then $L_{s+1} = u$ independently of d_{s+1} . If $d_{s+2} \neq 0$ then $L_{s+2} = u + 1 = \lfloor (s+2+1)/2 \rfloor$ and

we can replace s by $s + 2$. Hence we can assume that $d_{s+2} = 0$, so that $L_{s+2} = u$ and for some $t \geq 2$, $L_{s+1} = \dots = L_{s+t} = u$. If $n - 1 = s + t$, the result clearly holds. Otherwise, we can assume that $L_{s+t+1} \neq u$. Then $d_{s+t+1} \neq 0$ and $L_{s+t+1} = u + t$. Assume for the moment that $n - 1 \geq s + 2t$. Since $u + t = \max\{u + t, s + 2t - (u + t)\}$, we have $L_{s+t+1} = \dots = L_{s+2t} = u + t$ and $L_{s+2t} = \lfloor (s + 2t + 1)/2 \rfloor$. Now $\sum_{j=s+1}^{s+2t} L_j = tu + t(u + t)$ while

$$\begin{aligned} \sum_{j=s+1}^{s+2t} \lfloor (j+1)/2 \rfloor &= \sum_{k=0}^{t-1} (\lfloor (s+t-k+1)/2 \rfloor + \lfloor (s+t+1+k+1)/2 \rfloor) \\ &= \sum_{k=0}^{t-1} ((s+t-k+1)/2 + (s+t+1+k+1)/2 - 1/2) \\ &= t(2u+t) \end{aligned} \tag{2}$$

where the equality (2) follows since $s + t \pm k$ have the same parity, so that the two numerators have opposite parity. Thus $s + 2t$ is stable. By induction there is a maximal stable j . If $n - 1$ is stable, we are done. Otherwise, if $n - 1 = s + t + 1 + m$ for $0 \leq m < t - 1$, then the pairs with indices $s + t - k, s + t + 1 + k$ for $k = 0, \dots, m$ still satisfy (2), while each of the remaining terms $L_j = u$ for $j = s + 1, \dots, s + t - m - 1$ is less or equal to the corresponding $\lfloor (j + 1)/2 \rfloor$. ∞

3 Worst-case analyses

3.1 The Berlekamp-Massey Algorithm

First we rewrite this algorithm slightly:

ALGORITHM 3.1 ([5, p. 124])

Input: $n \geq 1$, sequence (S_0, \dots, S_{n-1}) over \mathbb{F} .

Output: L_n and connection polynomial $c = 1 + c_1X + \dots + c_rX^r \in \mathbb{F}[X]$ of (S_0, \dots, S_{n-1}) , $r \leq L_n$.

Auxiliaries: $c', t \in \mathbb{F}[X]$, $d, d' \in \mathbb{F} \setminus \{0\}$, integer e .

$L := 0$; $c := 1$; $e := 1$; $c' := 1$; $d' := 1$;

for $i := 0$ to $n - 1$ do

$d := \sum_{j=0}^L c_j \cdot S_{i-j}$;

if $(d = 0)$ $e := e + 1$;

else if $(2L > i)$ $\{ c := c - (d/d') \cdot X^e c'; e := e + 1; \}$

else $\{ L := i + 1 - L; t := c; c := c - (d/d') \cdot X^e c'; c' := t; d' := d; e := 1; \}$

return L, c .

PROPOSITION 3.2 *If (S_0, \dots, S_{n-1}) is a sequence of elements from a field \mathbb{F} , the Berlekamp-Massey Algorithm requires at most $2B_n - n + 1$ multiplications.*

PROOF. For $0 \leq i \leq n-1$, we write L_{i+1} and $c^{(i+1)}$ for the $(i+1)^{st}$ connection polynomial formed at the end of iteration i from $c^{(i)}$ and $c'^{(i)}$. Computing the discrepancy requires at most $\sum_{i=0}^{n-1} L_i \leq B_n$ multiplications. For additional multiplications to accrue, we need $\deg(c'^{(i)}) > 0$ for $i \geq j > 0$. Now $c^{(0)} = 1 = c'^{(0)}$ and $e > 0$, so $c'^{(i)}$ always has constant term 1. Also, $\deg(c^{(i)}) \leq L_i$ and $\deg(c'^{(i)}) > 0$ implies that $\deg(c'^{(i)}) < \deg(c^{(i)})$. So at most $\sum_{i=j}^{n-1} (\deg(c'^{(i)}) \leq \sum_{i=j}^{n-1} (\deg(c^{(i)}) - 1)$ additional multiplications can occur, for some j . Examination of the initial iterations shows that the minimal value of j is 3, with $\deg(c^{(1)}) = \deg(c^{(2)}) = 1$ and $\deg(c^{(3)}) = 2$ (and $c'^{(3)} = 1 - S_0X$). This gives at most an additional

$$\sum_{i=3}^{n-1} (\deg(c^{(i)}) - 1) = \sum_{i=0}^{n-1} \deg(c^{(i)}) - \sum_{i=0}^2 \deg(c^{(i)}) - n + 3 \leq B_n - n + 1.$$

∞

3.2 Algorithm MR

We recall some of the key notions which underly the main constructive result of [9], Theorem 7.3.

Let R be a commutative integral domain with $1 \neq 0$. A finite sequence over R is written (S_0, \dots, S_m) with $m \leq 0$ (so the length of the sequence is $1-m$). Then (S_0, \dots, S_m) satisfies a linear recurrence of order d if for some monic $f \in R[X]$ with $\deg(f) = d$, $S_j = -f_{d-1}S_{j+1} + \dots + f_0S_{j+d}$ for $m \leq j \leq -d$ (and $d \geq 1 - m$ is allowed).

With $S = S_0 + \dots + S_mX^m \in R[X^{-1}]$, this is equivalent to $(f \cdot S)_j = 0$ for $m + \deg(f) \leq i \leq 0$ for some monic f , where \cdot denotes multiplication in $R[X^{-1}, X]$. We call such an f an annihilator of (S_0, \dots, S_m) , without insisting that f be monic. Clearly f extends to an annihilator of (S_0, \dots, S_{m-1}) if and only if the obstruction $\mathcal{O}f \stackrel{\text{defn}}{=} (f \cdot S')_{m-1+\deg(f)} \in R$ vanishes, where $S' = S + S_{m-1}X^{m-1}$. Two annihilators of (S_0, \dots, S_m) were constructed inductively from first principles in [9, Section 4] using commutators $[\mathcal{O}f, S_0], [\mathcal{O}f, \mathcal{O}g] \in R$ for certain annihilators f, g .

For any $f \in R[X]$ the polynomial $\beta(f, S) = \sum_{i=1}^{\deg(f)} (f \cdot S)_i X^i \in XR[X]$ plays a useful role in developing the theory. Clearly f is an annihilator of (S_0, \dots, S_m) if and only if $f \cdot S = \beta(f, S)$. Further, if f is monic, the first $1 - m$ coefficients of $\beta(f, S)/f \in R[[X^{-1}]]$ coincide with the original sequence (see [9, Proposition 2.12]).

A non-zero annihilator of (S_0, \dots, S_m) is minimal if its degree is minimal. We write $\mu^{(m)}$ for a typical minimal polynomial of (S_0, \dots, S_m) and κ_m for $\deg(\mu^{(m)})$; in the notation of Section 1, $\kappa_m = L_{1-m}$. For example, if $(S_0, \dots, S_m) = (0, \dots, 0, 1)$, we can take $\mu^{(m)} = X^{1-m}$.

The inductive proof that the second construction yields a minimal polynomial required the key notion of the antecedent α_{m+1} of κ_{m+1} , defined when $\kappa_0 < \kappa_{m+1}$ (so $m + 1 < 0$); α_{m+1} is the smallest value of i , $m + 1 < i \leq 0$ such that $\kappa_i < \kappa_{m+1}$, [9, Definition 5.2]. (We think of $\mu^{(\alpha_{m+1})}$ as a 'best previous minimal polynomial' with $\deg(\mu^{(\alpha_{m+1})}) < \deg(\mu_{m+1})$.) The minimality of

the constructions was proved in [9, Proposition 5.1, 5.3], which have the following immediate consequence

COROLLARY 3.3 (*Cf. [5, Theorem 2]*) *If $\mathcal{O}\mu^{(m+1)} \neq 0$ for some $\mu^{(m+1)}$ then*

$$\deg(\mu^{(m)}) = \max\{\deg(\mu^{(m+1)}), 1 - m - \deg(\mu^{(m+1)})\}.$$

Motivated by Mathematical Systems Theory, we called $(f, \beta(f, S))$ a realization of (S_0, \dots, S_m) ; if further $\deg(f)$ is minimal, we call $(f, \beta(f, S))$ a minimal realization (MR) of (S_0, \dots, S_m) . It follows that minimal realization is closely related to rational approximation with minimal-degree denominator. We write an MR of (S_0, \dots, S_m) as $\bar{\mu}^{(m)} = (\mu^{(m)}, \beta^{(m)})$. It was shown that $\beta^{(m)}$ could also be constructed inductively in [9, Section 6].

Finally, in [9, Theorem 7.3], the two inductive MR constructions were simplified and combined by

- (i) supressing α_{m+1} and using $\mu^{(\alpha_{m+1})}$ instead;
- (ii) subsuming the case $m+1 \leq 0$ and $\kappa_{m+1} = \kappa_0$ by defining $\bar{\mu}^{(\alpha_{m+1})}$ to be $(0, -X)$ if $S_0 = 0$ and $(1, 0)$ otherwise; see [9, Definition 7.2];
- (iii) using the variable $d_{m+1} \stackrel{\text{defn}}{=} 2\kappa_{m+1} + m - 1$, which satisfies $d_{m+1} < 0$ if and only if $\kappa_m = 1 - m - \kappa_{m+1} > \kappa_{m+1}$ if and only if $\bar{\mu}^{(\alpha_m)}$ must be updated (by $\bar{\mu}^{(m+1)}$).

This combined construction directly suggested the body of Algorithm MR (writing current values $\bar{\mu}^{(\alpha_{m+1})}$, $\mathcal{O}\mu^{(\alpha_{m+1})}$ and d_{m+1} as $\bar{\mu}'$, \mathcal{O}' and d respectively) as well as how to initialize the algorithm, [9, Section 7.2]. (We have negated $\bar{\mu}$ so that $\mu^{(m)} = X^{1-m}$ if $(S_0, \dots, S_m) = (0, \dots, 0, 1)$.)

ALGORITHM 3.4 (*[7, 9, Algorithm MR]*)

Input: $m \leq 0$, R an integral domain, $(S_0, \dots, S_m) \in R$.

Output: $\bar{\mu}$, an MR for (S_0, \dots, S_m) .

Auxiliaries: MR's $\bar{\mu}'$, $\bar{t} \in R[X] \times XR[X]$, $\mathcal{O}, \mathcal{O}' \in R \setminus \{0\}$, integer d .

$\bar{\mu} := (1, 0)$; $\bar{\mu}' := (0, -X)$; $\mathcal{O}' := 1$; $d := -1$;

for $i := 0$ downto m do

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    {  $\mathcal{O} := \sum_{j=0}^{\deg(\mu)} \mu_j \cdot S_{i+\deg(\mu)-j}$ ;                               /* compute  $\mathcal{O}$  */
      if  $(\mathcal{O} \neq 0)$  { if  $(d < 0)$  {  $d := -d$ ; swap( $\bar{\mu}, \bar{\mu}'$ ); swap( $\mathcal{O}, \mathcal{O}'$ ); } /* update  $\bar{\mu}'$ ,  $\mathcal{O}'$  */
                           $\bar{\mu} := \mathcal{O} \cdot X^d \bar{\mu}' - \mathcal{O}' \cdot \bar{\mu}$ ; } /* update  $\bar{\mu}$  */
       $d := d - 1$ ; } /* update  $d$  */

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return $\bar{\mu}$.

PROPOSITION 3.5 *Let (S_0, \dots, S_m) be a sequence of elements from a domain R and $n = 1 - m$. The number of R -multiplications required to compute a minimal polynomial is at most $3B_n + 2n - 7$ and to compute an MR is at most $5B_n + n - 6$.*

PROOF. For $m \leq i \leq 0$, $\bar{\mu}^{(i)}$ is obtained using $\mathcal{O}_i = \mathcal{O}\mu^{(i+1)}$, d_{i+1} , $\bar{\mu}^{(i+1)}$, \mathcal{O}'_{i+1} and $\bar{\mu}^{(i+1)}$. Computing \mathcal{O}_i requires at most $\sum_{i=0}^m (\kappa_{i+1} + 1) = \sum_{i=0}^{n-1} L_i + n \leq B_n + n$ multiplications. To maximise the number of updating multiplications, we want $\mathcal{O}_i \neq 0$ for $m \leq i \leq 0$. Initially, we have $\bar{\mu}^{(0)} = (X, S_0X)$, $\bar{\mu}'^{(0)} = (1, 0)$ and $d_0 = 0$; then $\bar{\mu}^{(-1)} = (-S_0X + S_{-1}, -S_0^2X)$ and $d_{-1} = -1$. Next, $\mathcal{O}_{-2} = S_{-1}^2 - S_0S_{-2}$, $\bar{\mu}^{(-2)} = \mathcal{O}'_{-1}X\bar{\mu}^{(-1)} - \mathcal{O}_{-2}(1, 0)$ and $\bar{\mu}'^{(-2)} = \bar{\mu}^{(-1)}$.

For computing minimal polynomials, $\bar{\mu}^{(0)}$ and $\bar{\mu}^{(-1)}$ require no multiplications and $\mu^{(-2)}$ at most 2. For $m \leq i \leq -3$, $1 \leq \deg(\mu^{(i+1)}) \leq \deg(\mu^{(i+1)}) - 1$, giving at most $\sum_{i=j}^m (\deg(\mu^{(i+1)}) + \deg(\mu^{(i+1)}) + 2)$ more multiplications. In all therefore, there are at most

$$2 + \sum_{i=-3}^m (2\kappa_{i+1} + 1) = 2 \left(\sum_{i=0}^m \kappa_{i+1} - \sum_{i=0}^{-2} \kappa_{i+1} \right) - m \leq 2B_n + n - 7.$$

For computing an MR, $\beta^{(-1)} = S_0^2X$ and $\beta^{(-2)} = \mathcal{O}'_{-1}X\beta^{(-1)}$ each require at most one multiplication. In general, $\deg(\beta^{(i+1)}) \leq \deg(\mu^{(i+1)})$ and $X|\beta^{(i+1)}$. Similarly for $\beta'^{(i+1)}$. Hence this updating requires at most another

$$2 + \sum_{i=-3}^m (\deg(\beta'^{(i+1)}) + \deg(\beta^{(i+1)})) \leq 2 + \sum_{i=-3}^m (2\kappa_{i+1} - 1) \leq 2B_n - n + 1$$

for a total of at most $5B_n + n - 6$ multiplications. \(\times\)

4 A monic Algorithm MR

When $R = GF(2)$, Algorithm MR clearly computes a monic minimal polynomial, the multiplications reduce to additions and the updating becomes:

$$\text{if } \left(\sum_{j=0}^{\deg(\mu)} \mu_j \cdot S_{i+\deg(\mu)-j} \neq 0 \right) \{ \text{if } (d < 0) \{ d := -d; \text{swap}(\bar{\mu}, \bar{\mu}'); \} \bar{\mu} := \bar{\mu} + X^d \bar{\mu}'; \}.$$

We now show how to compute a monic minimal polynomial when R is a field \mathbb{F} in such a way that the polynomials μ' , β' (of strictly smaller degree) are multiplied by an element of \mathbb{F} .

THEOREM 4.1 *Let (S_0, \dots, S_m) be a sequence over a field \mathbb{F} . Put*

$$\begin{aligned} \bar{\mu}^{(0)} &= (1, 0), & \bar{\mu}^{(\alpha_0)} &= (0, -X) \text{ and } \mathcal{O}\mu^{(\alpha_0)} = 1 & \text{if } S_0 = 0 \\ \bar{\mu}^{(0)} &= (X, S_0X), & \bar{\mu}^{(\alpha_0)} &= (1, 0) \text{ and } \mathcal{O}\mu^{(\alpha_0)} = S_0 & \text{if } S_0 \neq 0. \end{aligned}$$

For $m \leq i \leq -1$ let $\bar{\mu}^{(i)} \in \mathbb{F}[X]$ be defined inductively by $\bar{\mu}^{(i)} = \bar{\mu}^{(i+1)}$ if $\mathcal{O}\mu^{(i+1)} = 0$ and

$$\bar{\mu}^{(i)} = \begin{cases} \bar{\mu}^{(i+1)} - q_i \cdot X^{d_{i+1}} \bar{\mu}^{(\alpha_{i+1})} & \text{if } d_{i+1} \geq 0 \\ X^{-d_{i+1}} \bar{\mu}^{(i+1)} - q_i \cdot \bar{\mu}^{(\alpha_{i+1})} & \text{if } d_{i+1} < 0 \end{cases}$$

otherwise, where $q_i = \mathcal{O}\mu^{(i+1)}/\mathcal{O}\mu^{(\alpha_{i+1})}$. Then $\bar{\mu}^{(i)}$ is a monic MR and

$$\bar{\mu}^{(\alpha_i)} = \begin{cases} \bar{\mu}^{(\alpha_{i+1})} & \text{if } d_{i+1} \geq 0 \\ \bar{\mu}^{(i+1)} & \text{if } d_{i+1} < 0 \end{cases} \quad d_i = \begin{cases} d_{i+1} - 1 & \text{if } \mathcal{O}\mu^{(i+1)} = 0 \\ |d_{i+1}| - 1 & \text{otherwise.} \end{cases}$$

PROOF. It was noted in [9] that the initial values are natural. The proof that $\bar{\mu}^{(i)}$ is as claimed is by induction on i . Assume that $\mu^{(j)}$ is monic for $i+1 \leq j \leq 0$ and that $\mathcal{O}\mu^{(i+1)} \neq 0$. Since a non-zero multiple of an MR is clearly an MR, [9, Theorem 7.3](i) implies that $\bar{\mu}^{(i)}$ is an MR and we need only show that $\bar{\mu}^{(i)}$ is monic.

We consider two cases: $\kappa_{i+1} = \kappa_0$ and $\kappa_{i+1} > \kappa_0$. If $\kappa_0 = \kappa_{i+1}$, then as in the proof of *loc. cit.*, Theorem 7.3(i), $\mu^{(i)}$ is precisely the minimal polynomial of [9, Proposition 5.3] made monic, and we are done.

Suppose now that $\kappa_{i+1} > \kappa_0$, so that $\mu^{(\alpha_{i+1})} \neq 0$. Put $a = \alpha_{i+1}$. If $d_{i+1} < 0$ then $\mu^{(i)}$ is monic since $\mu^{(i+1)}$ is monic and $-d_{i+1} + \deg(\mu^{(i+1)}) > \deg(\mu^{(i+1)}) > \deg(\mu^{(a)})$. For $d_{i+1} \geq 0$, we show that $\deg(\mu^{(i+1)}) > d_{i+1} + \deg(\mu^{(a)})$, which will imply that $\mu^{(i)}$ is monic.

By construction, we have $i+1 < a \leq 0$ and $\deg(\mu^{(i+1)}) = \deg(\mu^{(a-1)}) > \deg(\mu^{(a)})$. Now $\deg(\mu^{(a-1)}) = 1 - (a-1) - \deg(\mu^{(a)})$ by Corollary 3.3. Thus $\deg(\mu^{(i+1)}) = 2 - a - \deg(\mu^{(a)})$ and $d_{i+1} = 2\deg(\mu^{(i+1)}) + i - 1 = 4 - 2a - 2\deg(\mu^{(a)}) + i - 1$. Hence if $\deg(\mu^{(i+1)}) \leq d_{i+1} + \deg(\mu^{(a)})$, then $2 - a - \deg(\mu^{(a)}) \leq 3 - 2a - \deg(\mu^{(a)}) + i$ and $a \leq i+1$, for a contradiction. The remainder of the proof is the same as part (ii) of *loc. cit.*, Theorem 7.3. \square

As in *loc. cit.*, Section 7.2, Theorem 4.1 yields

ALGORITHM 4.2 (*monic Algorithm MR*) (cf. [1, p. 184], [5, p. 124].)

Input: $m \leq 0$, sequence (S_0, \dots, S_m) over \mathbb{F} .

Output: $\bar{\mu}$, a monic MR for (S_0, \dots, S_m) .

Auxiliaries: MR's $\bar{\mu}', \bar{t} \in \mathbb{F}[X] \times X\mathbb{F}[X]$, $\mathcal{O}, \mathcal{O}' \in \mathbb{F} \setminus \{0\}$, integer d .

$\bar{\mu} := (1, 0)$; $d := -1$; $\bar{\mu}' := (0, -X)$; $\mathcal{O}' := 1$;

for $i := 0$ downto m do

$\mathcal{O} := \sum_{j=0}^{\deg(\mu)} \mu_j \cdot S_{i+\deg(\mu)-j}$;

if $(\mathcal{O} \neq 0)$ { if $(d \geq 0)$ $\bar{\mu} := \bar{\mu} - (\mathcal{O}/\mathcal{O}') \cdot X^d \bar{\mu}'$;

else { $d := -d$; $\bar{t} := \bar{\mu}$; $\bar{\mu} := X^d \bar{\mu} - (\mathcal{O}/\mathcal{O}') \cdot \bar{\mu}'$; $\bar{\mu}' := \bar{t}$; $\mathcal{O}' := \mathcal{O}$; }

$d := d - 1$; }

return $\bar{\mu}$.

We show the algorithm at work when $\mathcal{O}_i \neq 0$ for $i = 0, -1, -2$. Writing $q_i = \mathcal{O}_i/\mathcal{O}'_{i+1}$, we have $\mathcal{O}_0 = S_0$, $\bar{\mu}^{(0)} = (X, q_0X)$, $\bar{\mu}'^{(0)} = (1, 0)$, $\mathcal{O}'_0 = S_0$ and $d_0 = 0$. Next, $\mathcal{O}_{-1} = S_{-1}$, $\bar{\mu}^{(-1)} = (X - q_{-1}, q_0X)$, $\bar{\mu}'^{(-1)} = (1, 0)$ and $d_{-1} = -1$. On the third iteration, $\mathcal{O}_{-2} = S_{-2} - S_{-1}^2/S_0$,

$\bar{\mu}^{(-2)} = (X^2 - q_{-1}X - q_{-2}, q_0X^2)$, $\bar{\mu}'^{(-2)} = (X - q_{-1}, q_0X)$ and $d_{-2} = 0$. Note that the only multiplication is to compute \mathcal{O}_{-2} .

The reader may check that when $\mathbb{F} = GF(2)$, the updating of $\bar{\mu}$ and $\bar{\mu}'$ in the monic version reduces to that given at the beginning of this section.

PROPOSITION 4.3 *Let (S_0, \dots, S_m) be a sequence of elements from a field \mathbb{F} and $n = 1 - m$. The number of \mathbb{F} -multiplications required to compute a monic minimal polynomial is at most $2B_n - n$ and to compute a monic MR is at most $3B_n - 2n$.*

PROOF. This is similar to the proof of Proposition 3.5. Computing \mathcal{O}_i requires at most $\sum_{i=0}^m \kappa_{i+1} = \sum_{i=0}^{n-1} L_i \leq B_n$ multiplications since $\mu^{(i+1)}$ is monic. To maximise the multiplications arising during updating, we want $\mathcal{O}_i \neq 0$ for $m \leq i \leq 0$. None arise for $i = 0, -1, -2$ and for $i \leq -3$, $1 \leq \deg(\mu'^{(i+1)}) \leq \deg(\mu^{(i+1)}) - 1$, so computing $\mu^{(m)}$ requires at most $\sum_{i=-3}^m (\kappa_{i+1} - 1) \leq B_n - n$ multiplications. Similarly, computing $\beta^{(m)}$ requires at most $\sum_{i=-3}^m \deg(\mu'^{(i+1)}) \leq B_n - n$ multiplications. ⊠

Appendix: Three remarks on [4]

According to [4, p.209], the number of multiplications required by the Berlekamp-Massey algorithm for a sequence of length $n \geq 1$ over a field \mathbb{F} is

$$\begin{cases} W_n = n(n+1)/2 & \text{at worst} \\ A_{q,n} = n(n+1)/2 - q^{-1}n^2/4 + o(q^{-2}) & \text{on the average,} \end{cases}$$

where the average is for uniformly and independently distributed (u.i.d.) sequences and $|\mathbb{F}| = q$. Both results were proved using the Berlekamp-Massey algorithm.

1. It was claimed on [4, p. 209] that W_n is a tight upper bound, but $W_n = 2B_n - n + 1 + \lfloor (3n-1)/2 \rfloor$ and so it cannot be tight.
2. Since $A_{q,n} + o(q^{-1}) = W_n = 2B_n - n + 1 + \lfloor (3n-1)/2 \rfloor$, we have $2B_n - n \geq A_{q,n} > 2B_n - n$. Thus the value of $A_{q,n}$ found in [4] is incorrect.
3. The proof of [4, Proposition 1] used the Berlekamp-Massey algorithm under the hypothesis that 'there is one formula for a sequence of length zero'. We now give an elementary inductive proof of [4, Proposition 1], independent of any particular algorithm and which avoids 'sequences of length zero'. Our inductive basis is simply that for $n = 1$, there is a unique sequence of linear complexity 0 and that there are $q - 1$ sequences of linear complexity 1. We then continue with Definition 2.1 and elementary properties of linear complexity.

Proposition Let \mathbb{F} be a field with q elements and $n \geq 1$. If sequences of length n are u.i.d., then

$$\Pr[L_n = L] = \begin{cases} 0 & \text{if } L < 0 \\ q^{-n} & \text{if } L = 0 \\ q^{2L-n-1}(q-1) & \text{if } 1 \leq L \leq \lfloor n/2 \rfloor \\ q^{n-2L}(q-1) & \text{if } \lfloor n/2 \rfloor < L \leq n \\ 0 & \text{if } L > n. \end{cases}$$

PROOF. Clearly $\Pr[L_n = L] = 0$ for $L < 0$ or $L > n$. It is convenient to put $N(n, L) = |\{(S_0, \dots, S_{n-1}) : L_n = L\}|$. We will show by induction on n that $N(n, L)$ coincides with the stated probabilities multiplied by q^n . Let $n = 1$. It is clear that $S_0 = 0$ is the unique sequence with $L_1 = 0$ and that there are $q - 1$ sequences S_0 of complexity 1, which agrees. Suppose inductively that the result is true for sequences of length $n - 1 \geq 1$. We consider three cases.

(a) $L = 0, n$. Let $L = 0$. Then clearly $N(n, L) \geq 1$. If $L_n(S_0, \dots, S_{n-1}) = 0$ then (S_0, \dots, S_{n-2}) is the all-zero sequence by the inductive hypothesis since $0 \leq L_{n-1} \leq L_n = L$ and so $N(n, L) = 1$. Suppose now that $L = n$. We show that $N(n, L) = q - 1$. If (S_0, \dots, S_{n-2}) is the all-zero sequence and $d_n = S_{n-1} \neq 0$ then $L_n = n$, so $N(n, L) \geq q - 1$. Moreover, $L_{n-1} \leq n - 1$ and $n = L_n = \max\{L_{n-1}, n - L_{n-1}\}$ forces $L_{n-1} = 0$, so (S_0, \dots, S_{n-2}) is the all-zero sequence. Thus $N(n, n) = q - 1$.

(b) $1 \leq L \leq \lfloor n/2 \rfloor$. Suppose first that $2L \leq n - 1$. Then $L_{n-1} \leq L_n = L \leq \lfloor (n - 1)/2 \rfloor$ and we can apply the inductive hypothesis to any (S_0, \dots, S_{n-2}) . If S_{n-1} is such that $d_n = 0$ for some (S_0, \dots, S_{n-2}) , then $1 \leq L = L_n = L_{n-1} \leq \lfloor (n - 1)/2 \rfloor$, and we obtain $N(n - 1, L) = q^{2L-1}(q - 1)$ sequences in this way. We also have $L < n - L$, so L cannot result from some (S_0, \dots, S_{n-2}) with $d_n \neq 0$. Thus $N(n, L) = N(n - 1, L) = q^{2L-1}(q - 1)$ as required.

Suppose now that $2L = n$. Then $L > \lfloor (n - 1)/2 \rfloor$. If S_{n-1} is such that $L_n = L$ and $d_n = 0$, the inductive hypothesis yields $N(n - 1, L) = q^{2(n-1-L)}(q - 1)$ sequences. There are also $(q - 1)N(n - 1, L) = q^{2(n-1-L)}(q - 1)^2$ sequences resulting from $d_n \neq 0$. Thus

$$N(n, L) = N(n - 1, L) + (q - 1)N(n - 1, L),$$

and substituting the inductive values and $n = 2L$ yields the result.

(c) $\lfloor n/2 \rfloor < L \leq n$. Then $(n - 1)/2 < L$ and $\max\{L, n - L\} = L$. If S_{n-1} is such that $d_n = 0$, then $\lfloor (n - 1)/2 \rfloor < L = L_{n-1} \leq n - 1$ and we can apply the inductive hypothesis to (S_0, \dots, S_{n-2}) , giving $N(n - 1, L) = q^{2(n-1-L)}(q - 1)$ sequences. We also get a sequence of complexity L if $d_n \neq 0$ and either (i) $L_{n-1} = L$ or (ii) $L_{n-1} = n - L$. Since $\lfloor (n - 1)/2 \rfloor < L = L_{n-1} \leq n - 1$, (i) gives $(q - 1)N(n - 1, L) = q^{2(n-1-L)}(q - 1)^2$ sequences. For (ii), we have $1 \leq n - L \leq \lfloor (n - 1)/2 \rfloor$ and so we obtain an additional $(q - 1)N(n - 1, n - L) = q^{2(n-L)-1}(q - 1)^2$ sequences. Thus

$$N(n, L) = N(n - 1, L) + (q - 1)N(n - 1, L) + (q - 1)N(n - 1, n - L)$$

and on substituting the inductive values, we easily get $N(n, L) = q^{2(n-L)}(q - 1)$ as required.

For an equivalent result derived from the number of sequences (S_0, \dots, S_{n-1}) over \mathbb{F} with prescribed linear and jump complexity, see [6].

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We take this opportunity to correct several typographical errors in [9]:

p. 335, line 7: delete $\epsilon(g) + \deg(g) \leq -m$

p. 336, lines 2,3 should read $\mathcal{O}(X^2 - X) = ((X^2 - X) \circ \mathcal{F}'_{-3+2} = \mathcal{F}'_{-3} - \mathcal{F}'_{-2} = 1$

p. 336 line 13 $n < m$ should be $m \leq n$.

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