Exact computations with quasiseparable matrices
Clément Pernet, Hippolyte Signargout, Gilles Villard

To cite this version:

HAL Id: hal-03978799
https://cnrs.hal.science/hal-03978799
Submitted on 8 Feb 2023

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L’archive ouverte pluridisciplinaire HAL, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d’enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.
Exact computations with quasiseparable matrices

Clément Pernet
Grenoble INP, Univ. Grenoble Alpes
CNRS, LJK, UMR 5224
Grenoble, France

Hippolyte Signargout
ENS de Lyon, U. Lyon, CNRS, Inria,
UCBL, LIP UMR 5668 Lyon and LJK
UMR 5224 Grenoble, France

Gilles Villard
CNRS, U. Lyon, Inria, ENS de Lyon,
UCBL, LIP UMR 5668
Lyon, France

ABSTRACT
Quasi-separable matrices are a class of rank-structured matrices widely used in numerical linear algebra and of growing interest in computer algebra, with applications in e.g. the linearization of polynomial matrices. Various representation formats exist for these matrices that have rarely been compared.

We show how the most central formats SSS and HSS can be adapted to symbolic computation, where the exact rank replaces threshold based numerical ranks. We clarify their links and compare them with the Bruhat format. To this end, we state their space and time cost estimates based on fast matrix multiplication, and compare them, with their leading constants. The comparison is supported by software experiments.

We make further progresses for the Bruhat format, for which we give a generation algorithm, following a Crout elimination scheme, which specializes into fast algorithms for the construction from a sparse matrix or from the sum of Bruhat representations.

KEYWORDS
Quasiseparable matrix, SSS, HSS, Bruhat generator

1 INTRODUCTION
Quasiseparable matrices arise frequently in various problems of numerical analysis and are becoming increasingly important in computer algebra, e.g. by their application to handle linearizations of polynomial matrices [2]. Structured representations for these matrices and their generalisations have been widely studied but to our knowledge they have not been compared in detail with each other. In this paper we aim to adapt SSS [9] and HSS [5, 16], two of the most prominent formats of numerical analysis to exact computations and compare them theoretically and experimentally to the Bruhat format [21]. These formats all have linear storage size in both the dimension and the structure parameter. We do not investigate the Givens weight representation [7] as it strongly relies on orthogonal transformations in $\mathbb{C}$, which transcription in the algebraic setting is more challenging. See [13, 25, 26] for an extensive bibliography on computing with quasiseparable matrices.

Definition 1.1. An $n \times n$ matrix $A$ is $s$-quasiseparable if for all $k \in [1, n]$, $\text{rank}(A_{1:k,k+1:n}) \leq s$ and $\text{rank}(A_{k+1:n,1:k}) \leq s$.

Complexity bound notation. We consider matrices over an abstract commutative field $K$, and count arithmetic operations in $K$. Our detailed comparison of formats aims in particular to determine the asymptotic multiplicative constants, an insightful measure on the algorithm’s behaviour in practice. In this regard, we will use the leading term in the complexities as the measure for our comparison: namely a function $T_{XXX}(n,s)$ such that the number of field operations for running Algorithm XXX with parameters $n, s$ is $T_{XXX}(n,s) + o(T_{XXX}(n,s))$ asymptotically in $n$ and $s$. We proceed similarly for the space costs with the notation $S_{XXX}(n,s)$. We denote by $\omega$ a feasible exponent for square matrix multiplication, and $C_\omega$ the corresponding leading constant; namely, using above notation, $T_{MM}(n) = C_\omega n^{\omega}$, where $MM$ corresponds to the operation $C = C + AB$ with $A, B, C \in K^{m \times n}$. The straightforward generalization gives $T_{RF}(m,k,n) = C_\omega mnk \min(m,k,n)^{\omega-3}$ for the product of an $m \times k$ by a $k \times n$ matrix.

1.1 Rank revealing factorizations
Space efficient representations for quasiseparable matrices rely on rank revealing factorizations: a rank $r$ matrix $A \in K^{m \times n}$ is represented by two matrices $L \in K^{m \times r} R \in K^{r \times n}$ such that $A = LR$. In exact linear algebra, such factorizations are usually computed using Gaussian elimination, such as PLUQ, CUP, PLE, CRE decompositions [8, 15, 24], which we will generally denote by $RF$.

Cost estimates of the above factorization algorithms are either given as $O(mnr^{\omega-2})$ or with explicit leading constants $T_{RF}(m,n,r) = K_m r^{\omega}$ under genericity assumptions: $m = n = r$ and generic rank profile [8, 15]. We refer to [20] for an analysis in the non-generic case of the leading constants in the cost of the two main variants of divide and conquer Gaussian elimination algorithms. We may therefore assume that $T_{RF}(m,n,r) = C_{RF} mnr^{\omega-2}$ for a constant $C_{RF}$, for $\omega \geq 1 + \log_2 3$, which is the case for all practical matrix multiplication algorithms. Note that for $\omega = 3$, these costs are both equal to $2mnr$. Unfortunately, the non-predictable rank distribution among the blocks being processed leads to an over-estimation of some intermediate costs which forbids tighter constants (i.e. interpolating the known one $K_3 = 2/3$ in the generic case). The algorithms presented here still carry on for smaller values of $\omega$, but we chose to skip the more complex derivation of estimates on their leading constants for the sake of clarity.

Our algorithms for SSS and HSS can use any rank revealing factorization. On the other hand, the Bruhat format requires one revealing the additional information of the rank profile matrix, e.g. the CRE decompositions used here (See [8]).

Theorem 1.2 ([8, 17]). Any rank $r$ matrix $A \in K^{m \times n}$ has a CRE decomposition $A = CRE$ where $C \in K^{m \times r}$ and $E \in K^{r \times n}$ are in column and row echelon form, and $R \in K^{r \times n}$ is a permutation matrix.

The costs we give in relation to Bruhat generator therefore rely on constants $C_{RF}$ from factorizations allowing to produce a CRE decomposition, like the ones in [20].

1.2 Contributions
In Section 2 we define the SSS, HSS and Bruhat formats. We then adapt algorithms operating with HSS and SSS generators from the literature to the exact context. The HSS generation algorithm is given in a new iterative version and the SSS product algorithm has an improved cost. We focus for SSS on basic bricks on which other
operations can be built. This opens the door to adaptation of fast algorithms for inversion and system solving [3, 4, 10] and format modeling operations such as merging, splitting and model reduction [4]. In Section 3.3 we give a generic Bruhat generation algorithm from which we derive new fast algorithms for the generation from a sparse matrix and from a sum of matrices in Bruhat form.

Table 1 displays the best cost estimates for different operations on an \( n \times n \) s-quasi-separable matrix in the three formats presented in the paper. The best and optimal storage size is reached by the Bruhat format which also has the fastest generator computation algorithm. However, this is not reflected in the following operation costs as applying a quasiseparable matrix to a dense matrix is least expensive with an SSS generator and addition and product of \( n \times n \) matrices given in Bruhat form is super-linear in \( n \). We notice in Proposition 2.5 that SSS is twice as expensive as SSS and gives no advantage in our context. We thus stop the comparison at the generator computation. We still give in Table 1 the cost of generator and addition and product as applying a quasiseparable matrix to a dense matrix gives no advantage in our context.

Table 1: Summary of operation and storage costs

<table>
<thead>
<tr>
<th>Operation</th>
<th>SSS</th>
<th>HSS</th>
<th>Bruhat</th>
</tr>
</thead>
<tbody>
<tr>
<td>Storage</td>
<td>7ns</td>
<td>18ns</td>
<td>4ns</td>
</tr>
<tr>
<td>Gen. from Dense ( \times ) Dense block vector (( n \times n ))</td>
<td>2C_{RF}n^2s^{3s-2} + 2\omega C_{RF}n^2s^{3s-2}</td>
<td>2C_{RF}n^2s^{3s-2} + 8C_{RF}ns^{3s-2}</td>
<td>7ns</td>
</tr>
<tr>
<td>Addition</td>
<td>(10 + 2\omega)C_{RF}ns^{3s-1}</td>
<td>(8 + 2\omega)C_{RF}ns^{3s-1} + 2C_{RF}n^2s^{3s-2}</td>
<td>36n^2s + \frac{2\omega n^2 s^2}{\log n/s} + 24n^2s^2 n/s</td>
</tr>
<tr>
<td>Product</td>
<td>(31 + 2\omega)C_{RF}ns^{3s-1}</td>
<td>(31 + 2\omega)C_{RF}ns^{3s-1} + 2C_{RF}n^2s^{3s-2}</td>
<td>78n^2</td>
</tr>
</tbody>
</table>


PROPOSITION 2.2. Any \( n \times n \) s-quasiseparable matrix has an s-SSS representation. It uses \( S_{SSS}(n, s) = 7n^2 \) field elements.

PROOF. Direct consequence of Proposition 3.1. \( \square \)

### 2.2 HSS generators

The HSS format was first introduced in [6], although the idea originated with the uniform \( H \)-matrices of [12] and in more details with the \( H^2 \)-matrices of [14], with algorithms relying on [23]. The \( H^2 \) format is slightly different from HSS, more details in [13].

The format is close to SSS (see Proposition 2.4) as the way of defining blocks is similar. Yet, the slicing grid is built recursively and the definition of blocks product depends on the path to follow in the recursion tree. Also, both sides of the diagonal are treated jointly and the format is therefore less compact, which as will be shown makes HSS less efficient.

The structure is complex and notations differ in the literature. We made the following choices: we avoid the recursive tree definition inherited from the Fast Multipole Method [6] and thus only consider constant-depth recursive block divisions. We made this choice to focus on linear algebra and quasiseparable matrices with no prerequisites (no notion of where the rank is). For the same reason we focus on uniform subdivisions. Most literature on HSS uses non-uniform grids in order to adapt to matrices with a structure within the quasiseparable rank structure [6]. Despite being more general, this adds confusion which is not needed in our case.

We use a notation similar to [27] with transition matrices.

**Definition 2.3.** Let \( A \in \mathbb{K}^{n \times n} \) and the uniform block divisions

\[
A \equiv \begin{bmatrix}
A_{1,1} & \cdots & A_{1,K} \\
\vdots & \ddots & \vdots \\
A_{K,1} & \cdots & A_{K,K}
\end{bmatrix},
\]

\( A \) is given in hierarchically semi-separable format of order \( t \) (t-HSS) if it is given by the \( t \times t \) matrices \((L_{i,j}, D_i) \) \( i \in [1, n] \) and \( k \in [1, K] \) \( D_i \) and if we define recursively for \( K - 1 \) to 1 and \( i \in [1, 2^K] \),

\[
U_k = \begin{bmatrix} U_k^{1,2i-1} & U_k^{1,2i-1} \end{bmatrix} \quad \text{and} \quad V_k = \begin{bmatrix} V_k^{1,2i-1} & V_k^{1,2i-1} \end{bmatrix}
\]

then

\[
A_{k,2i-1} = U_k^{1,2i-1}B_{k,2i-1}V_k^{1,2i-1} \\
A_{k,2i} = U_k^{1,2i-1}B_{k,2i-1}V_k^{1,2i-1}
\]
The HSS generator can be seen as a recursive SSS generator with two differences: the use of the 8 matrices, and the distribution of the translation matrices. The similarity is made clear in Proposition 2.4.

Proposition 2.4. Let $U_{K;J}$, $V_{K;J}$, $D_i$, $R_{K;J}$, $W_k$, $b_{K;J}$, for appropriate $k \leq K$, $i \leq 2^k$ be a $t$-HSS generator for $A$. Let $I, J \in \{1, 2^k\}$ and $k$ the highest level of recursion for which $A_{K;J}$ is not included in a diagonal block. For $i_1 = \lceil \frac{j}{2^{K-k-1}} \rceil$, $i_0 = \lceil \frac{j}{2^{K-k}} \rceil$ and $j_1 = \lceil \frac{j}{2^{K-k-1}} \rceil$ we have

$$A_{K;J} = U_{K;J} R_{K;J} \cdots R_{K+1;J} b_{K;J} W_{K;J_1} V_{K;J_1}.$$  

Proof. By induction on Equation (3).

Proposition 2.5. Any $n \times n$ $s$-quasiseparable matrix has a $2s$-HSS representation. This is the optimal block parameter and the representation uses $s_{HSS}(n,s) = 18ns$ field elements.

Proof. Consequence of Proposition 3.2. For optimality let $A$ be $s$-quasiseparable given in $t$-HSS form. We use Proposition 2.4:

$$[A_{K;3\ldots4\ldots5\ldots6}] = [U_{K;3\ldots4\ldots5\ldots6}] [H]$$

where $H \in K^{T \times s}$. The quasi-separability of $A$ bounds the rank of the left part of Eq. (5) by $2s$ while the one of the right side is bounded by $t$. When the first bound is tight we get $t \geq 2s$.

2.3 Bruhat generators

The Bruhat generator was first defined in [19, 21]. Contrarily to SSS and HSS, it does not use on a pre-defined grid but relies on the rank profile information contained in the rank profile matrix $[8]$ of the lower and upper triangular parts of the quasiseparable matrix.

Recall from [21] that a matrix is $t$-overlapping if any subset of $t + 1$ of its non-zero columns (resp. rows) contains at least one whose leading non-zero element is below (resp. before) the trailing non-zero element of another. We call $\mathcal{J}_n$ the anti-identity matrix of dimension $n$ and define the Left operator $\mathcal{L} : K^{n \times n} \rightarrow K^{n \times n}$ s.t.

$$\mathcal{L}(A)_{ij} = \begin{cases} A_{ij} & \text{if } i + j \leq n \\ 0 & \text{otherwise} \end{cases}$$

Definition 2.6. An $n \times n$ matrix $A$ is represented in $t$-Bruhat format if it is given by a diagonal matrix $D \in K^{n \times n}$ and 6 matrices $C(L), R(L), E(L), C(U), R(U), E(U)$ where $C(L) \in K^{n \times n}$ and $C(U) \in K^{n \times n}$ are in column echelon form and $t$-overlapping, $E(L) \in K^{n \times n}$ and $E(U) \in K^{n \times n}$ are in column echelon form and $t$-overlapping and $R(L) \in K^{n \times n}$, $R(U) \in K^{n \times n}$ are permutation matrices and satisfy

$$A = D + \sum_{j=0}^{N} \mathcal{L}(C(L) R(L) E(L)) + \mathcal{L}(C(U) R(U) E(U)) \mathcal{J}_n$$

Proposition 2.7. Any $n \times n$ $s$-quasiseparable matrix has an $s$-Bruhat representation. It uses $s_{Bruhat}(n,s) = 4ns$ field elements which is optimal.

Proof. By [21, Theorem 29]. As $2ns$ coefficients are necessary to represent all rank $s$ triangular matrices, $4ns$ is optimal.

3 CONSTRUCTION OF THE GENERATORS

3.1 SSS generator from a dense matrix

We recall in Algorithm DenseToSSS the construction of an SSS generator from a dense $s$-quasiseparable matrix $A \in K^{n \times n}$. It is adapted from [4, §6.1] and [10, Alg. 6.5] where the SVD based numerical rank revealing factorizations are replaced by RF.

The blocks $D_i$ are directly extracted from the dense matrix in Line 3. Each block-triangular part is then compressed independently. Each step eliminates a chunk made of a block-row of $A$ and a remainder from the previous step. The result is three blocks of the generator and a remainder to be eliminated at the subsequent step.

Algorithm 3.1 DenseToSSS

Input: $A$ an $n \times n$ dense-sparse matrix with $s \leq t$
Output: $F_t, Q_t, R_t, U_t, V_t, W_t, D_t$ for appropriate $i \in \{1, N\}$ a t-SSS representation of $A$
1. $A = \begin{bmatrix} \cdots & A_{i,1} & \cdots \\ & \ddots & \vdots \\ \cdots & \cdots & A_{i,N} & \cdots \end{bmatrix}$, $H = \begin{bmatrix} H_{t,1} & \cdots & H_{t,N} \end{bmatrix}$ \leftarrow 0
2. for $k = 1 \ldots N - 1$ do
3. \hspace{0.5em} $D_k \leftarrow A_{k,k}$
4. \hspace{0.5em} $\begin{bmatrix} W_k \\ U_k \end{bmatrix} \leftarrow \text{RF} \left( \begin{bmatrix} H_{k,1} & \cdots & H_{k,K} \end{bmatrix} \right)$
5. \hspace{0.5em} $\begin{bmatrix} Q_{k+1} \\ H_{k+1,0} \\ \vdots \\ H_{k+1,N} \end{bmatrix} \leftarrow \text{RF} \left( \begin{bmatrix} H_{k+1,0} & \cdots & A_{k+1,N} \end{bmatrix} \right)$
6. $D_N = A_{N,N}$

Proposition 3.1. Algorithm DenseToSSS computes a $t$-SSS generator for an $s$-quasiseparable matrix ($s \leq t$) in $T_{DenseToSSS}(n,t) = 2C_{RF}n^2s^{o-2}$ field operations.

Proof. For $k \in \{1, N-1\}$, the dimensions of the output of Lines 4 and 5 are sufficient since the input of the factorisation is a concatenation of a block of $A$ with a rank-revealing factor of another block of $A$ on the same side of the diagonal, and is hence of rank at most $s$.

Let $i, j \in \{1, N\}$. If $i = j$ Line 3 for $k = i$ gives $D_i = A_{i,i}$. If $i < j$, Line 4 gives

$$W_{j-1} V_j = H_{j-2,j}$$

$$W_k H_{k,j} = H_{k-1,j}$$

$$U_i H_{i,j} = A_{i,j}$$

$$U_i V_{i+1} = A_{i,i+1}$$

which combines to

$$U_i W_{i+1} \cdots W_j V_j = A_{i,j}. \text{The same way, if } i > j \text{ then } P_j R_{j-1} \cdots R_{j+1} Q_j = A_{i,j}.$$ The cost is $\Sigma_{k=1}^{N-1} 2 \text{Tr} (f(N-k), 2t, s) = 2C_{RF}n^2s^{o-2}$. □

3.2 HSS generator from a dense matrix

The first construction algorithm for a general quasiseparable matrix is presented in [6]. We present in Algorithm DenseToHSS an iterative version of the faster and simpler algorithm of [27].

Each step of the loop on $k$ passes block-row-wise and block-column-wise on the matrix inherited from the previous step, factorising block rows and block columns two by two. At each step
each block is hence factorised twice, producing transition matrices \( R \) and \( W \), the remainder being either passed to the following step or finally stored as a \( B \) matrix.

**Algorithm 3.2 DenseToHSS**

*Input:* An \( n \times n \) quasiseparable matrix of order \( s \)

*Output:* \( U_{K,i}, V_{K,j}, D_1, R_{K,i}, W_{K,j}, B_{K,i} \) for appropriate \( k \leq K, i, j \leq 2^k \) a \( t \)-HSS representation of \( A \) with \( t \geq 23 \)

1. \( H \leftarrow A \) \quad ➔ Use the block division of Eq. (2) with \( k = K \)
2. for \( i = 1 \ldots 2^K \) do
3. \( D_i \leftarrow A_{K,i,i} \)
4. for \( k = K \ldots 1 \) do
5. for \( i = 1 \ldots 2^k \) do
6. \( \begin{cases} \text{if } H_{k+1,i+1,j} \neq 0 \text{ then } & \begin{pmatrix} H_{k+1,i+1,j}^{-1} & H_{k+1,i+1,j}^{-1} \\ H_{k+1,i+1,j}^{-1} & H_{k+1,i+1,j}^{-1} \end{pmatrix} \\ \text{end if} \end{cases} \)
7. \( \text{end for} \)
8. for \( i = 1 \ldots 2^k \) do
9. \( B_{k+1,i} \leftarrow H_{k+1,i,2i} \)
10. \( B_{k+1,i} \leftarrow H_{k+1,i,2i} \)
11. for \( j = 1 \ldots 2^k \) do
12. \( H_{k-1,i,j} = \begin{cases} H_{k-1,i,j}^{-1} & H_{k-1,i,j}^{-1} \\ H_{k-1,i,j}^{-1} & H_{k-1,i,j}^{-1} \end{cases} \)
13. \( \text{end for} \)
14. for \( i = 1 \ldots 2^k \) do
15. \( U_{K,i} \leftarrow B_{K,i+1,i} \)
16. \( V_{K,i} \leftarrow B_{K,i+1,i} \)

**Proposition 3.2.** Algorithm DenseToHSS computes a \( t \)-HSS generator for an \( s \)-quasiseparable matrix if \( 2s \leq t \in C_{RF} n^2 s^{2s-2} \) field operations. For \( t = 2s \), this is \( T_{\text{DenseToHSS}}(n,s) = 2s C_{RF} n^2 s^{2s-2} \).

**Proof.** Let \( k \in [1,K], j \neq j \in [1,2]^k \). The dimensions of the output in Lines 6 and 7 is sufficient since the matrices being factorized are each time a concatenation of two blocks of rank at most \( s \) and are hence rank of rank at most \( 2s \leq t \). If \( i = j = 1 \), the instructions give

\[
H_{k,i,j} = \begin{bmatrix} R_{k+1,i,j} & B_{k,i} & W_{k+1,i,j} \\ R_{k+1,i,j}^{-1} & W_{k+1,i,j} \end{bmatrix}.
\]

(11)

Otherwise,

\[
H_{k,i,j} = \begin{bmatrix} R_{k+1,i,j} & B_{k,i} & W_{k+1,i,j} \\ R_{k+1,i,j}^{-1} & W_{k+1,i,j} \end{bmatrix}.
\]

(12)

Let now \( I, J \in [1,N] \). If \( I = J \), Line 3 gives \( D_i = A_{K,i,J} \). Otherwise, let \( k \) be the highest level of recursion for which \( A_{K,i,j} \) is not included in a diagonal block. From Line 1, \( A_{K,i,J} = H_{K,i,J} \). Equation (12) can be used \( k - k \) times, together with Line 12 to get

\[
A_{K,i,J} = \begin{bmatrix} R_{k+1,i,j} & \cdots & B_{k+1,i,j} & W_{k+1,i,j} \end{bmatrix}.
\]

(13)

where \( i_1 = [1/2^k-k] \), \( j_1 = [1/2^k-k] \), and \( i_2 = [1/2^k-k] \). \( R_{k+1,i,j} \) and \( B_{k+1,i,j} \) can be replaced in Eq. (13) using Lines 15 and 16 and Eq. (11) (from the definition of \( k \) we have \( |i_1 - j_1| = 1 \)) in order to get Eq. (4); this concludes the proof of correctness.

Line 6 at \( k < K \) and \( i \) performs a rank revealing decompositions on an input formed by the \( 2t \times (i - 1) \) block \( H_{k+1,i,1} \) and the \( 2t \times 2t(2^{k+1} - i) \) block \( H_{k,i+1,2^k} \) at cost \( T_{RF}(1(2^{k+1} - i), 2t, t) \). The cost is equal for Line 7. The overall cost is then \( \sum_{t=1}^{2s} \sum_{i=1}^{2s} 4C_{RF}(2^{k+1} - i)t^{2} \leq 2^{s+2} C_{RF} n^2 s^{2s-2} \).

Because the blocks of each side of the defined by the same matrices, Algorithm DenseToHSS and any HSS construction algorithm applies rank revealing factorisations on blocks with rank bounded by \( 2s \) for \( s \)-quasiseparable matrices instead of \( s \) in Algorithm DenseToHSS. The optimal HSS block size of \( s \)-quasiseparable matrices is thus \( 2s \), which makes HSS less efficient in terms of storage and operation cost.

As the costs are higher and HSS has the same drawbacks as SSS, namely needing a fixed slicing grid and a previously computed quasiseparability order, we do not detail more algorithms for HSS. For information in the numerical context we mainly refer to [16, 22]. Note that faster construction algorithms exist, probabilistic in [18] and with constraints on the input in [6].

### 3.3 Bruhat generator from a dense matrix

The construction of a Bruhat generator from a dense matrix is achieved by [21, Alg. 12] run twice, once for each of the upper and lower triangular parts of the input matrix, and the diagonal matrix \( D \) is directly extracted from the dense matrix.

We give in Algorithm LBRUHATGEN an updated version of [21, Alg. 12], where Schur complement computations are delayed until they are needed. This allows for faster computations when the input is not given as a dense matrix and will be used for computing the sum of two matrices in Bruhat form and generators from a sparse matrix.

Algorithm LBRUHATGEN can be given any input format, provided we have a way to compute for any submatrix \( B \) of the input matrix

1. \( \text{CRE}(B,G,H) \) a CRE decomposition of \( B = GH^T \)
2. \( \text{for } R \) a set of indices, \( B_{K,R} \) and \( B_{S,R} \) the rows and columns of \( B \) with indices in \( R \)

We use the notation TRSM for Triangular Solve Matrix: \( \text{TRSM}(L,A) \) outputs \( L^{-1}A \) for \( L \) triangular.

**Proposition 3.3.** An \( s \)-Bruhat generator can be computed from an \( n \times n \) dense \( s \)-quasiseparable matrix in \( T_{\text{DenseToB}}(n,s) = C_{RF} n^2 s^{2s-2} \).

**Proof.** Algorithm LBRUHATGEN is adapted from [21, Alg. 12]; we therefore refer to the proof of [21, Theorem 24] for its correctness. Apart from the order in which they are made, the operations are the same in both algorithms when the input is dense and the cost is hence the same. Computing a Bruhat generator from a dense matrix is two applications of Algorithm LBRUHATGEN. The cost satisfies:

\[
T_{\text{LB}}(n,s) \leq C_{RF}/4n^2 s^{2s-2} + 2 T_{\text{LB}}(n/2,s) \leq C_{RF}/2n^2 s^{2s-2}.
\]

### 3.4 Bruhat generator from a sparse matrix

In applications, matrices are often presented in a sparse structure. In order to detect and/or harness their quasiseparable structure, it
Algorithm 3.3 LBRUHATGEN

Input: \( A \in K^{m \times m} \) left triangular \( s_A \)-quasiseparable
Input: \( G, H \in K^{n \times n} \)
Output: \( C, R, E \) a left-Bruhat generator for \( A - \mathcal{D}(GH^T) \)
1: Split \( A = \begin{bmatrix} A_{(1)}^{(1)} & A_{(1)}^{(2)} \\ A_{(2)}^{(1)} & A_{(2)}^{(2)} \end{bmatrix}, G = \begin{bmatrix} G^{(1)} \\ G^{(2)} \end{bmatrix}, H = \begin{bmatrix} H^{(1)} \\ H^{(2)} \end{bmatrix} \) where
2: \( A_{(1)}^{(1)} \in K^{n \times m} \times \overline{R} \)
3: \( C \leftarrow \text{CRE}(A^{(1)}_{(1)}, G^{(1)}, H^{(1)}) \)
4: \( R \leftarrow \text{BRP}(C_0); C \leftarrow \text{CRP}(E_0); r_0 \leftarrow \#R \)
5: \( L \leftarrow A_{(2)}^{(1)} - G_{R^*}^{(1)} H^{(2)T}_{R^*} \)
6: \( X \leftarrow A_{(2)}^{(1)} - G_{R^*}^{(1)} H^{(2)T}_{R^*} \)
7: \( B^{(12)} \leftarrow \mathcal{D}(\text{TRSM}(L, X))_{R^*} \)
8: \( Y \leftarrow A_{(2)}^{(2)} - G^{(2)} H^{(1)T} \)
9: \( B^{(21)} \leftarrow \mathcal{D}(\text{TRSM}(U, Y))_{C^*} \)
10: \( C_1, R_1, E_1 \leftarrow \text{LBRUHATGEN}(A^{(1)}_{(2)} + C^{(2)}_{(1)} + H^{(1)T} C^*, B^{(12)} + G^{(2)} H^{(2)T} s_{C^*} C) \)
11: \( C_2, R_2, E_2 \leftarrow \text{LBRUHATGEN}(I_{(2)} \leftarrow A^{(2)}_{(2)} + C^{(2)}_{(1)} + H^{(1)T} C^*, B^{(12)} + G^{(2)} H^{(2)T} s_{C^*} C) \)
12: \( P_{01} \leftarrow \) the permutation which sorts the rows of \( E_0 \) and \( E_1 \) by increasing column of pivot
13: \( P_{02} \leftarrow \) the permutation which sorts the columns of \( C_0 \) and \( C_2 \) by increasing row of pivot
14: \( C \leftarrow \begin{bmatrix} C_0 & C_2 \\ B^{(12)} R^*_1 & C_1 \end{bmatrix} \begin{bmatrix} P_{01} & \\ I & \end{bmatrix} \)
15: \( R \leftarrow \begin{bmatrix} R_0 & R_1 \\ R_2 & I \end{bmatrix} \begin{bmatrix} P_{01} & \\ I & \end{bmatrix} \)
16: \( E \leftarrow \begin{bmatrix} E_0 & E_1 \\ R_0^* B^{(12)} & I \end{bmatrix} \begin{bmatrix} P_{01} & \\ I & \end{bmatrix} \)
17: return \( C, R, E \)

is crucial to exploit the sparsity in the construction of the quasiseparable generators.

For the construction of a Bruhat generator, the generic algorithm Algorithm LBRUHATGEN can be applied on a sparse matrix, provided two operations are specialized:

1. The extraction of a subset of \( s \) rows or columns into a dense format, which is straightforward for a sparse matrix;
2. The computation of a CRE decomposition, which is specialized in Algorithm SparseCRE which in turn uses Algorithm SparseRankProfiles

Lemma 3.4. Algorithm SparseRankProfiles is correct with probability at least \( 1 - 2r/|S| \) and runs in \( T_{\text{SparseRankProfiles}}(n, r) = 2(C_{oo} + C_{RF}) n^r s^{r-1} + 2r|A| \) field operations for \( s + t \leq r \).

Proof. Applying the Toeplitz pre-conditioners in Lines 3 and 4 costs \( \frac{n^r s^{r-1}}{T} O(r) \) which is dominating by \( n^r s^{r-1} \).

Algorithm 3.4 SparseCRE

Input: \( A \in K^{m \times m} \) a rank \( \leq s \) sparse matrix
Input: \( G, H \in K^{n \times n} \)
Output: \( C, R, E \) such that \( A = \text{CRE} + GH^T \)
1: \( R, C \leftarrow \text{SparseRankProfiles}(A, G, H) \)
2: \( P = \begin{bmatrix} I_{R^*} & I_{C^*} \\ I_{R^*} & I_{C^*} \end{bmatrix} \\ Q = I_{C^*} I_{C^*} \)
3: \( M^{(11)} \leftarrow A^{(11)} - G^{(1)} H^{(1)T} \)
4: \( 
5: \( \) \)
6: \( L, R, U \leftarrow \text{DenseCRE}(M^{(11)}) \)
7: \( C \leftarrow \text{TRSM}(L, M^{(12)}) \)
8: \( D \leftarrow \text{TRSM}(A^{(21)}, U^T) \)
9: \( E \leftarrow \begin{bmatrix} U & R^T C \end{bmatrix} Q^T \)
10: \( C \leftarrow P^T \begin{bmatrix} L \\ DR^T \end{bmatrix} \)
11: return \( C, R, E \)

Proposition 3.5. Algorithm SparseCRE computes a CRE decomposition of \( A - GH^T \) with probability at least \( 1 - 2r/|S| \) in \( T_{\text{SparseCRE}}(n, r) = 2(C_{oo} + C_{RF}) n^r s^{r-1} + 2r|A| \) field operations for \( s + t \leq r \).

Proof. Let \( \rho \) be the rank of \( A - GH^T \).
\[
T_{\text{SparseCRE}}(n, r, \rho) = 2T_{\text{MR}}(n, r, \rho) + T_{\text{CRE}}(\rho, \rho, \rho) + 2T_{\text{TRSM}}(n - \rho, \rho) + T_{\text{SparseSep}}(n, \rho) \leq n^r s^{r-1} \left( 4C_{oo} + \frac{2C_{oo}}{2^{r-1} - 2} + C_{RF} \right) + 2r|A|.
\]

Proposition 3.6. Algorithm LBRUHATGEN computes a Left-Bruhat generator from an sparse \( s \)-quasiseparable matrix \( A \in K^{n \times n} \) in \( T_{\text{SPGen}}(n, s, |A|) = \frac{2^{r+1} - 9}{2^{r-1} - 2} C_{oo} + C_{RF} \) \( n s^r - 1 \log n/s + 2s|A| \) field operations with probability at least \( 1 - 2n/|S| \).
We recall the algorithm of \cite[§2]{4} for computing the product. We study here the application of an SSS \(~\mbox{generator}\) to a block of \(~v\) vectors \(~B\in \mathbb{K}^{n \times v}\). We give the costs for \(~v \leq s\) (they can be otherwise deduced by slicing \(~B\) in blocks of \(~s\) columns).

\subsection{SSS \times dense}

We here recall the algorithm of \cite[§2]{4} for constructing the product of an SSS matrix with a dense matrix \((\mbox{independently published in} \ [10, \mbox{Alg. 7.1}])\). For simplicity, Algorithm \textsc{LowSSSxDense} only detail the computations with a strictly lower-block-triangular SSS matrix, that is a matrix whose SSS representation is zero except for the \(~P_i, Q_i\) and \(~R_i\). Extrapolating from there to the product with any SSS matrix can be done by transposing the algorithm for the upper-block-triangular part, and adding the product with the block-diagonal matrix made of the \(~D_i\).

\begin{algorithm}[h]
\caption{LowSSSxDense}
\begin{algorithmic}
\State \textbf{Input:} \(P_i, Q_i, R_i\) for \(i \in [1, N]\) an \(s\)-SSS generator for a strictly lower-block-triangular matrix \(A\); \(B\) and \(C\) dense \(n \times v\) matrices
\State \textbf{Output:} \(C = AB\)
\State 1: \(\text{Split} \ B = \begin{bmatrix} B_1 \\ \vdots \\ B_N \end{bmatrix}, C = \begin{bmatrix} C_1 \\ \vdots \\ C_N \end{bmatrix} \mbox{ in } s \times s \mbox{ blocks}\)
\State 2: \(H_1 \leftarrow Q_1 B_1\)
\For {\(i = 2 \ldots N\)}
\State 3: \(H_i \leftarrow Q_i B_i + R_i H_{i-1}\)
\State 4: \(C_i \leftarrow C_i + P_i H_{i-1}\)
\EndFor
\end{algorithmic}
\end{algorithm}

\begin{proposition}
\text{The product of an} \(n \times n\) \mbox{matrix given by its} \(s\)-SSS \mbox{generator with an} \(n \times v\) \mbox{dense matrix with} \(v \leq s\) \mbox{can be computed in} \(15\) \(\mbox{for the diagonal blocks and two applications of Algorithm \textsc{LowSSSxDense} in which each step costs} \(3C_{\omega} s^2 d^{\omega - 2}\).
\end{proposition}

\begin{proposition}
\text{The product of an} \(n \times n\) \mbox{matrix given by its} \(s\)-Bruhat \mbox{generator by a dense} \(n \times v\) \mbox{matrix with} \(v \leq s\) \mbox{can be computed in} \(15\) \(\mbox{for the diagonal blocks and two applications of Algorithm \textsc{LowSSSxDense} in which each step costs} \(3C_{\omega} s^2 d^{\omega - 2}\).
\end{proposition}

\subsection{Experimental comparison}

Experimental results are given in Fig. 2 (Appendix A). As expected from Propositions 4.1 and 4.2 we obtain costs that are linear in \(s\); we can also observe the same slight dependance in \(r\) of the Bruhat cost as in Section 3.5. On the parameters we chose, SSS is about four times faster than Bruhat. This can be explained by the compactification of the Bruhat generator needed for the product. This operation is free of arithmetic operations and hence does...
not appear in the cost of Proposition 4.2 but the data transfers are non-negligible in practice.

5 SUM OF QUASISEPARABLE MATRICES

The sum and product of two quasiseparable matrices of order $s_B$ and $s_C$ are quasiseparable matrices of order at most $s_B + s_C$. In this section we show how to compute SSS and Bruhat generators for the sum of two quasiseparable matrices.

The result we give in Proposition 5.1 for the sum of matrices given in SSS form can only be used on two generators defined on the same grid. This is a drawback of most operations in SSS which is avoided with the Bruhat format. As a consequence, in a large sequence of operations, the SSS grid size needs to be chosen according to the maximal quasi-separability order among all intermediate results, while the Bruhat always fits to the current quasiseparable order. This can impact the overall cost. The slower original SSS format of [9] avoids this issue, at the expense of multiplying space and time costs by the quasiseparability order, as in [1, 2].

5.1 SSS sum

Consider two matrices $B$ and $C$ with the same order $s$. We first note that the concatenation of the blocks of both input generators leads to matrices which satisfy Eq. (1) for $A = C + B$ [4, §10.2].

Let $P_i^{(K)}, V_i^{(K)}, U_i^{(K)}, W_i^{(K)}$, $P_i^{(C)}, V_i^{(C)}, U_i^{(C)}, W_i^{(C)}$, for appropriate $i \in [1, N]$ be an $s$-SSS representation of $K$ for $K \in \{B, C\}$. The following matrices satisfy Eq. (1) with $A = B + C$, for appropriate $i \in [1, N]$.

$$P_i = \begin{pmatrix} P_i^{(B)} & P_i^{(C)} \end{pmatrix}, Q_i = \begin{pmatrix} Q_i^{(B)} & Q_i^{(C)} \end{pmatrix}, R_i = \begin{pmatrix} R_i^{(B)} & R_i^{(C)} \end{pmatrix}, \quad (16)$$

$$U_i = \begin{pmatrix} U_i^{(B)} & U_i^{(C)} \end{pmatrix}, V_i = \begin{pmatrix} V_i^{(B)} & V_i^{(C)} \end{pmatrix}, W_i = \begin{pmatrix} W_i^{(B)} & W_i^{(C)} \end{pmatrix}, \quad (17)$$

$$D_i = D_i^{(B)} + D_i^{(C)} \quad (18)$$

Such sets of matrices with these dimensions satisfying Eq. (1) will be called an $(s, 2s)$-SSS generator for $A$. The granularity of their description remains that of $s \times s$ blocks, but the dimension of the matrices in the representation is doubled and leads to a suboptimal storage size. A second step is therefore to use Algorithm SssCompression to obtain a $2s$-SSS generator for the sum and reduce the storage size by $4s(n - 2s)$.

**Proposition 5.1.** A $2s$-SSS representation of $B + C \in \mathbb{K}^{n \times n}$ can be computed from $s$-SSS representations of $B$ and $C$ in time

$$T_{SSS}(n, s) \equiv (10 + 2s) C_{ss} n^2 s^{o-1}. \quad (19)$$

**Proof.** For any $s \times s$ block $A_{ij}$ of $A = B + C$, it can be checked that the representation in the output of Algorithm SssCompression called on the generator of Section 5.1 matches. The additions of Eq. (18) are dominated by the call to Algorithm SssCompression whose cost is of $M$ steps with four $2s \times 2s$ by $2s \times 2s$ products, two $2s \times 2s$ square products, and two $s \times s$ by $2s \times s$ products.

Note that the $(s, 2s)$-SSS generator is intermediate between the SSS form and the original definition of quasiseparable matrices given in [9], where the generators are $s \times s$ matrices but the granularity of the description is of dimension 1.

Algorithm 5.1 SssCompression

**Input:** $P_i, Q_i, R_i, U_i, V_i, W_i, D_i$ for appropriate $i \in [1, N]$, an $(s, 2s)$-SSS generator for $A \in \mathbb{K}^{n \times n}$

**Output:** $P_i', Q_i', R_i', U_i', V_i', W_i', D_i'$ for appropriate $i \in [1, M]$, a $2s$-SSS representation of $A$ with $M = \lfloor N/2 \rfloor$

1. for $i \leftarrow 1 \ldots M$
2. $P_i' \leftarrow \begin{pmatrix} P_{2i-1} & P_{2i} \end{pmatrix}$
3. $Q_i' \leftarrow R_{2i}Q_{2i-1} - Q_{2i}$
4. $R_i' \leftarrow U_{2i-1}R_{2i-1} - R_{2i}$
5. $U_i' \leftarrow \begin{pmatrix} U_{2i-1}W_{2i-1} \end{pmatrix}$
6. $V_i' \leftarrow V_{2i-1}W_{2i-1} - V_{2i}$
7. $W_i' \leftarrow W_{2i-1}W_{2i}$
8. $D_i' \leftarrow \begin{pmatrix} D_{2i-1} & D_{2i} \end{pmatrix}$

5.2 Bruhat sum

As with SSS, the sum of two matrices in Bruhat form can be computed by first concatenation of both generators, then by retrieving the Bruhat format in a second step.

Given two left triangular matrices $A$ and $B$ given by Bruhat generators $C^{(A)}, R^{(A)}, E^{(A)}, C^{(B)}, R^{(B)}, E^{(B)}$, their sum indeed writes

$$A + B = \begin{pmatrix} C^{(A)} & C^{(B)} \end{pmatrix} \begin{pmatrix} R^{(A)} & R^{(B)} \end{pmatrix} \begin{pmatrix} E^{(A)} & E^{(B)} \end{pmatrix}. \quad (20)$$

A Bruhat generator for the right side in Eq. (20) can be obtained from a call to Algorithm LBruhatGen, viewed here as a compression algorithm. This relies on a specific CRE decomposition (Algorithm BruhatSumCRE), and on having $D_{\alpha\gamma}s$ for $D$ a submatrix of a sum given as in Eq. (20) and $\alpha$ a set of row indices (Proposition 5.3).

Algorithm 5.2 BruhatSumCRE

**Input:** $A, B \in \mathbb{K}^{n \times n}$ of rank at most $r_A$ and $r_B$, for generators $C^{(A)}, R^{(A)}, E^{(A)}, C^{(B)}, R^{(B)}, E^{(B)}$ s.t. $A = C^{(A)}R^{(A)}E^{(A)}$ and $B = C^{(B)}R^{(B)}E^{(B)}$ which are submatrices of Bruhat generators of matrices comprising $A$ and $B$

**Input:** $G, H \in \mathbb{K}^{n \times t}$

**Output:** $C, R, E$ such that $A + B = CRE + GH^T$

1. $C^{(R)}, R^{(R)}, E^{(R)} \leftarrow DenseCRE \left( \begin{pmatrix} R^{(A)}E^{(A)} \\ R^{(B)}E^{(B)} \end{pmatrix} \right)$
2. $C^{(L)}, R^{(L)}, E^{(L)} \leftarrow DenseCRE \left( \begin{pmatrix} C^{(B)}C^{(B)} G \end{pmatrix} \right)$
3. $X \leftarrow R^{(L)}E^{(L)}C^{(R)}R^{(R)}$
4. $C^{(X)}, R^{(X)}, E^{(X)} \leftarrow DenseCRE(X)$
5. $C \leftarrow C^{(L)}C^{(X)}$
6. $R \leftarrow R^{(X)}$
7. $E \leftarrow E^{(X)}E^{(R)}$

**Proposition 5.2.** Algorithm BruhatSumCRE computes a CRE decomposition of $A + B - GH^T$ in $T_{SumCRE}(n, r) = (3C_{ss} + 2C_{HF})n^2 s^{o-1}$ for $r_A + r_B + t \leq r$.

**Proof.** The matrices $C$ and $E$ are in column and row echelon form respectively as they are products of two echelon forms. The
cost is that of two dense CRE decompositions of size \( n \times (r_A + r_B + t) \) and products of an \( n \times (r_A + r_B + t) \) matrix by two \( (r_A + r_B + t) \times (r_A + r_B + t) \) and one \( (r_A + r_B + t) \times n \) matrices.

**Proposition 5.3.** For \( D \in K^{n \times n} \) a submatrix of the left-triangular part of a sum as in Eq. (20) and \( R \) a set of \( s \) row indices, \( D_{R,s} \) can be computed in \( T_{\text{S}+\text{S}}(n,s) = C_{\omega_1}s^{\omega_0-1} \).

Proof. There are at most \( s_A \) (resp. \( s_B \)) pivots of \( A \) (resp. \( B \)) impacting \( D \). We can thus write \( D = CRE + C \) made of \( n \) rows and \( s_A + s_B \) columns of \( \begin{bmatrix} C(A) & C(B) \end{bmatrix} \), \( R \) a permutation and \( E \) made of \( n \) columns and \( s_A \) rows of \( E(A) \) and \( s_B \) rows of \( E(B) \).

**Proposition 5.4.** The Bruhat form of the sum of two \( n \times n \) matrices of quaseparable order \( s_A \) and \( s_B \) in Bruhat form can be computed in \( T_{\text{BSS}}(n,s) = \left( \frac{9 \cdot 2^{n+1} - 4}{2^{n+2} - 1} \right) C_{\omega_1} + 2C_{\text{ref}} \) \( n^{\omega_0-1} \log n/s \) for \( s = s_A + s_B \).

Proof. Each lower and upper triangular part is converted to a left triangular instance and computed independently. Algorithm \text{LBruhatGen} is then called twice with \( t = 0 \) on an input matrix in factorized form as in (20).

The proof is the same as for Proposition 5.3 except that in the cost, the \( T_{\text{SparseCRE}} \) terms are replaced by \( T_{\text{Bruhat}}+T_{\text{S}+\text{S}} \) terms and the rows and columns of the submatrices are computed at a cost given by \( T_{\text{S}+\text{S}} \). Then we have

\[
T(n,s) \leq 2T(n/2,s) + T_{\text{BS}+\text{S}}(n/2,s) + 2T_{\text{S}+\text{S}}(n/2,s,s) + 2T_{\text{S}+\text{S}}(s,2s,n/2) + 2T_{\text{S}+\text{S}}(s,n/2) \leq 2T(n/2,s) + \left( \frac{9 \cdot 2^{n+1} - 4}{2^{n+2} - 1} \right) C_{\omega_1} + 2C_{\text{ref}} \) \( n^{\omega_0-1} \).

for one call to Algorithm \text{LBruhatGen}.

### 6 PRODUCT IN SSS

The product of two matrices given in SSS form uses two tricks we have seen previously. The first is to start by computing an \((s,2s)\) SSS representation before compression, as in the sum. Unlike the sum, computations are needed in addition to concatenation to get this representation. The second trick is to speed up these computations by using a Horner-like accumulation as in Algorithm \text{LowSSSSDense}. This accumulation will be done on both sides for the computation of all necessary products \( A_{i,k} B_{k,j} \) where \( A_{i,k} \) is under (resp. over) the diagonal and \( B_{k,j} \) is over (resp. under) it.

Algorithm \text{SSSS} details these computations, using the \( G_i \) and \( H_i \) as accumulators. It presents an improvement over the algorithm of [4, §3] and [10, Alg. 7.2]: 4 products have been avoided at each step by keeping them in memory in the \( T_i \) and \( S_i \). They can also be avoided in the numerical context.

**Theorem 6.1.** Algorithm \text{SSSS} computes a \((2s,2s)\) SSS generator for the product of two \( n \times n \) matrices given in \((s,2s)\) SSS form in

\[
T_{\text{SSSS}}(n,s) = (31 + 2^{n+1})C_{\omega_1}s^{\omega_0-1}. \tag{21}
\]

Proof. Using Lines 2 and 4 for \( G_i \) and Lines 10 and 14 for \( H_i \), induction on \( i \) shows that

\[
G_i = \sum_{k=1}^{i-1} P_{i-k}^{(A)} \cdots P_{k+1}^{(A)} Q_k^{(A)} T_k^{(B)} W_{k+1}^{(B)} \cdots W_{i-1}^{(B)} \tag{22}
\]

**Algorithm 6.1 SSSSS**

**Input:** For both \( M \in \{A, B\} \), \( P_i^{(M)}, Q_i^{(M)}, R_i^{(M)}, U_i^{(M)}, V_i^{(M)}, W_i^{(M)} \), \( D_i^{(M)} \) for appropriate \( i \in [1, N] \) an \( s\)-SSS generator for \( M \)

**Output:** A \( 2s\)-SSS generator for \( C = AB \)

\[ \text{All values not given as input are initialised to 0} \]

1. for \( i \leftarrow 1 \ldots N \) do
2. \( G_i \leftarrow Q_{i-1}^{(A)} U_{i-1}^{(B)} + T_{i-1}^{(B)} W_{i-1}^{(B)} \)
3. \( T_i \leftarrow R_i^{(A)} G_i \)
4. \( S_i \leftarrow P_i^{(A)} G_i \)
5. \( Q_i \leftarrow Q_i^{(A)} D_i^{(B)} + T_i^{(B)} V_i^{(B)} \)
6. \( R_i \leftarrow R_i^{(A)} P_i^{(B)} + 0 \)
7. \( U_i \leftarrow U_i^{(A)} D_i^{(A)} U_i^{(B)} + S_i W_i^{(B)} \)
8. \( W_i \leftarrow W_i^{(A)} V_i^{(A)} V_i^{(B)} \)
9. for \( i \leftarrow N \ldots 1 \) do
10. \( H_i \leftarrow V_{i+1}^{(A)} P_i^{(B)} + T_{i+1}^{(B)} R_i^{(B)} \)
11. \( T_i \leftarrow U_i^{(A)} H_i \)
12. \( D_i \leftarrow D_i^{(A)} D_i^{(B)} + S_i V_i^{(B)} + T_i Q_i^{(B)} \)
13. \( P_i^{C} \leftarrow D_i^{(A)} P_i^{(B)} + T_i R_i^{(B)} U_i^{(B)} \)
14. \( T_i \leftarrow W_i^{(A)} H_i \)
15. \( V_i \leftarrow V_{i+1}^{(A)} D_i^{(B)} + T_{i+1} Q_i^{(B)} \)
16. return \text{SssCompress}((P_i, Q_i, R_i, U_i, V_i, W_i, D_i)_{i \in [1, N]})

\[
H_i = \sum_{k=i+1}^{N} Z_{i+1}^{(A)} \cdots Z_{k-1}^{(A)} Z_k^{(A)} r_k^{(B)} u_k^{(B)} \cdots u_{i+1}^{(B)} \tag{23}
\]

Combining these results with Line 3 for \( S_i \), Line 11 for \( T_i \) and finally Line 12, we get that \( D_i^{(C)} = \sum_{k=i+1}^{N} \sum_{i \leq k \leq j} A_{i,k} B_{k,j} \). The equality

\[
U_{i}^{(C)} W_{i+1}^{(C)} \cdots W_{j-1}^{(C)} V_{j}^{(C)} = \sum_{k=1}^{N} A_{i,k} B_{k,j} \tag{24}
\]

and its counterpart when \( i > j \) can be checked with tedious but straightforward calculations.

The cost is that of \( 21 \) products and \( 8 \) sums of \( s \times s \) matrices at each of the \( N \) steps and on call to Algorithm \text{SssCompress}.

Again the result of Theorem 6.1 is limited to matrices defined on the same grid and the result always has the same storage size, whatever its quaseparability order. This is also true for product with HSS generators in numerical analysis [22]. The Bruhat format can avoid these issues, but to our knowledge no sub-quadratic algorithm exists for the product of two Bruhat generators. The method used for the sum in Section 5.2 opens the door towards a linear or quasi-linear product algorithm using Algorithm \text{LBruhatGen}. 
A EXPERIMENTS

We report here on experiments of an implementation of algorithms handling SSS and Bruhat generators over a finite field in the FFLAS-FFPACK library [11], at commit 33474931aa. This library provides efficient dense basic linear algebra routines, such as matrix multiplication, TRSM and Gaussian elimination revealing the rank profile matrix. It was compiled with the GNU C++ compiler g++ version 9.3.0 and linked with the OpenBLAS library version 0.3.8. The benchmarks are run on a single core of an Intel i5-7300U@2.6GHz running a Linux Mint-20 system.

For all experiments, the matrices have a fixed dimension $n = 3000$, over the finite field $\mathbb{Z}/131071\mathbb{Z}$. We draw the computation times depending on the quasiseparability orders, on three type of instances: having a ranks of their upper and lower triangular parts equal to 1000, 1500 and 1750.

Each point corresponds to the mean of the running times of 50 random instances with same parameters. Figure 1 compares the running times for the generation from a dense matrix. Figure 2 compares the running times for the product by a random dense $n \times 500$ block vector, using the same generators.

REFERENCES


Figure 2: Experimental timings for the computation of $\text{SSS}$ and $\text{Bruhat}$ times a dense matrix with $n = 3000$ and $v = 500$ over $\mathbb{Z}/131071\mathbb{Z}$.


