



Article Digital Signal Processing (DSP)-Oriented Reduced-Complexity Algorithms for Calculating Matrix–Vector Products with Small-Order Toeplitz Matrices

Janusz P. Papliński *[®], Aleksandr Cariow *[®], Paweł Strzelec and Marta Makowska

Faculty of Computer Science and Information Technology, West Pomeranian University of Technology, Żołnierska 49, 71-210 Szczecin, Poland

* Correspondence: janusz.paplinski@zut.edu.pl (J.P.P.); acariow@wi.zut.edu.pl or alexandr.tariov@zut.edu.pl (A.C.)

Abstract: Toeplitz matrix–vector products are used in many digital signal processing applications. Direct methods for calculating such products require N^2 multiplications and N(N - 1) additions, where N denotes the order of the Toeplitz matrix. In the case of large matrices, this operation becomes especially time intensive. However, matrix–vector products with small-order Toeplitz matrices are of particular interest because small matrices often serve as kernels in modern digital signal processing algorithms. Perhaps reducing the number of arithmetic operations when calculating matrix–vector products in the case of small Toeplitz matrices gives less effect than of large ones, but this problem exists, and it needs to be solved. The traditional way to calculate such products is to use the fast Fourier transform algorithm. However, in the case of small-order matrices, it is advisable to use direct factorization of Toeplitz matrices, which leads to a reduction in arithmetic complexity. In this paper, we propose a set of reduced-complexity algorithms for calculating matrix–vector products with Toeplitz matrices of order N = 3, 4, 5, 6, 7, 8, 9. The main emphasis will be on reducing multiplicative complexity since multiplication in most cases is more time-consuming than addition. This paper also provides assessments of the implementation of the developed algorithms on FPGAs.

Keywords: Toeplitz matrix; matrix-vector product; multiplication complexity

1. Introduction

Structured matrices possess some inherent structure or pattern, which can be exploited to develop faster and more efficient algorithms for computing with them. Computing with structured matrices typically involves developing specialized algorithms that take advantage of the underlying structure of the matrix to reduce the computational complexity of matrix operations. Many fast algorithms have been developed for computing with structured matrices [1-5]. These algorithms can significantly reduce the computation complexity when implementing operations with such matrices. The Toeplitz matrix occupies a special place among structured matrices. This is due to the widespread use of matrix-vector transforms associated with these matrices when solving various applied problems. They appear in many areas, like in approximation theory [6], compressive sensing [7], image processing [8–10], filtering and estimating [11,12], signal processing [7,13–15], statistics [16,17], time series analysis [18], acoustic echo cancellation and active noise control [19-21], cryptography [22-24], deep neural networks [25-31], and many other areas [32–38]. As for the operations of matrix–vector multiplication with smallorder Toeplitz matrices, they are, among other things, used in organizing the structures and computational processes of high-performance binary multipliers [22,39].

At present, a sufficient number of publications describe efficient methods for fast calculation of Toeplitz matrix–vector products [40–42]. Known fast algorithms are based



Citation: Papliński, J.P.; Cariow, A.; Strzelec, P.; Makowska, M. Digital Signal Processing (DSP)-Oriented Reduced-Complexity Algorithms for Calculating Matrix–Vector Products with Small-Order Toeplitz Matrices. *Signals* 2024, *5*, 417–437. https:// doi.org/10.3390/signals5030021

Academic Editor: Alexander Kocian

Received: 17 April 2024 Revised: 14 June 2024 Accepted: 18 June 2024 Published: 21 June 2024



Copyright: © 2024 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https:// creativecommons.org/licenses/by/ 4.0/). on embedding such a matrix in a $2N \times 2N$ circulant matrix and calculating the matrixvector product with the resulting matrix. Therefore, Toeplitz matrix–vector multiplication can be calculated as the product of a circulant matrix by a vector. This product can be computed using fast Fourier transform (FFT) algorithms [43]. These algorithms lead to data redundancy and require O(NlogN) operations [44]. However, this approach involves rather complicated housekeeping and a relatively large number of multiplications and additions. What is more, these operations are performed on complex numbers.

Alternative efficient algorithms for multiplying a Toeplitz/Hankel matrix by a vector not based on FFT were discussed in [45,46]. Both of these methods, based on the Karatsuba multiplication method [47], have a computational complexity of $O(N^{log_23})$ multiplications and use only real arithmetic. One way or another, well-known publications mainly describe general approaches to rationalizing the computations of Toeplitz matrix–vector products and practically do not consider examples of constructing such algorithms for specific N. At the same time, developing such algorithms for specific N is of independent interest since such algorithms can be used as building blocks, contributing to unification in designing more complex algorithms.

In this article, we propose and describe in detail new rationalized algorithms for matrix–vector multiplication for Toeplitz matrices of orders N = 3, 4, 5, 6, 7, 8, 9, which minimize the multiplication complexity compared to the conventional direct method, at the cost of some increase in additions. We emphasize that the reduced-complexity algorithm for the product of a matrix and a vector with a Toeplitz matrix for N = 2 is well-known in the literature and therefore is not considered here.

The remainder of this paper is organized as follows. Section 2 explains the preliminary information about Toeplitz matrices. Section 3 describes the proposed algorithms for orders from N = 3 to N = 9. Section 4 evaluates our algorithms in terms of computational cost. Section 5 concludes this paper.

2. Preliminary Remarks

The Toeplitz matrix is a structural one and has the same values on each diagonal:

$$\mathbf{\Gamma}_{N} = \begin{pmatrix} t_{N-1} & \dots & t_{1} & t_{0} \\ t_{N} & \dots & t_{2} & t_{1} \\ \vdots & \ddots & \ddots & \vdots \\ t_{2N-2} & \dots & t_{N} & t_{N-1} \end{pmatrix}.$$
(1)

The Toeplitz matrix-vector product can be represented as follows:

$$\mathbf{Y}_{N\times 1} = \mathbf{T}_N \mathbf{X}_{N\times 1},\tag{2}$$

where $\mathbf{X}_{N \times 1} = [x_0, x_1, \dots, x_{N-1}]^T$, $\mathbf{Y}_{N \times 1} = [y_0, y_1, \dots, y_{N-1}]^T$.

A direct application of the mathematical definition of matrix–vector multiplication (2), based on the multiplication of a dense matrix by a vector, yields an algorithm that, for real values, requires N^2 multiplications and N(N-1) additions. In the remainder of this article, such an algorithm will be referred to as the direct method, and the designated number of arithmetic operations will refer to the case where real values are used. In the general case of complex value calculations, the corresponding quantities correspond to complex multiplications and additions. The problem is to find a way to factorize the matrix that will lead to a reduction in computation, which has been undertaken using the relationships presented in the paper ([48]).

3. Algorithms for Toeplitz Matrix-Vector Multiplication

3.1. Algorithm for N = 3

Let it be necessary to calculate the matrix-vector product of the following form:

$$\begin{bmatrix} y_0 \\ y_1 \\ y_2 \end{bmatrix} = \begin{bmatrix} t_2 & t_1 & t_0 \\ t_3 & t_2 & t_1 \\ t_4 & t_3 & t_2 \end{bmatrix} \begin{bmatrix} x_0 \\ x_1 \\ x_2 \end{bmatrix}.$$
 (3)

The direct method of calculating the base matrix–vector product (3) requires 9 multiplications and 6 additions.

Proposition 1. *To calculate the product* (3)*, no more than 6 multiplications are required.*

Proof. Let us introduce auxiliary matrices: the matrix $P_{3\times 6}^{(3)}$ with the final summation operations performed to obtain the $Y_{3\times 1}$ signals and the matrix $T_{6\times 3}^{(3)}$ with the initial summation operations to prepare the corresponding signals to be multiplied by the diagonal matrix $D_6^{(3)}$, in which the entries are the algebraic sums of entries of the Toeplitz matrix T_3 . In this paper, in matrices containing summation, such as $P_{3\times 6}^{(3)}$ and $T_{6\times 3}^{(3)}$, all zeros are omitted to improve readability.

and

$$\mathbf{D}_{6}^{(3)} = \operatorname{diag}\left(s_{0}^{(3)}, s_{1}^{(3)}, \dots, s_{5}^{(3)}\right),$$

$$s_{0}^{(3)} = t_{2}, \quad s_{1}^{(3)} = -t_{2} - t_{3} + t_{4},$$

$$s_{2}^{(3)} = t_{3}, \quad s_{3}^{(3)} = -t_{1} + t_{2} - t_{3},$$

$$s_{4}^{(3)} = t_{1}, \quad s_{5}^{(3)} = t_{0} - t_{1} - t_{2}.$$
(4)

Taking into account the introduced matrix constructions, expression (2) can be written in the following form:

$$\mathbf{Y}_{3\times 1} = \mathbf{P}_{3\times 6}^{(3)} \mathbf{D}_{6}^{(3)} \mathbf{T}_{6\times 3}^{(3)} \mathbf{X}_{3\times 1},$$
(5)

where

$$\mathbf{X}_{3 \times 1} = [x_0, x_1, x_2]^T, \quad \mathbf{Y}_{3 \times 1} = [y_0, y_1, y_2]^T.$$

It is easy to see that the multiplicative complexity of calculating expression (5) is 6. The correctness of expression (5) is confirmed by the truth of the expression

$$\mathbf{T}_3 = \mathbf{P}_{3 \times 6}^{(3)} \mathbf{D}_6^{(3)} \mathbf{T}_{6 \times 3}^{(3)}$$

where T_3 is a 3 × 3 Toeplitz matrix (1). Expression (5) defines a reduced multiplicative complexity algorithm for calculating the matrix–vector product with a third-order Toeplitz matrix. \Box

Remark 1. The proposed algorithm (5) requires only 6 multiplications and 15 additions. In a number of practical applications, the entries of the Toeplitz matrix, i.e., t_0, t_1, \ldots, t_4 , are constant numbers. Then, the entries of the matrix $\mathbf{D}_6^{(3)}$ (4) can be calculated in advance and stored in the calculator's memory. For this case, the number of additions in the algorithm is reduced to 9. Thus, the proposed algorithm (5) applied to the calculation of the matrix–vector product (3) reduces 3 multiplication at the expense of 3 extra additions compared to the direct method.

Figure 1 shows the data flow diagram of the proposed algorithm (5). The initial and final additions follow from the matrices $\mathbf{P}_{3\times 6}^{(3)}$ and $\mathbf{T}_{3\times 6}^{(3)}$. The coefficients s_i are derived from the entries $s_i^{(3)}$ of the matrix $\mathbf{D}_6^{(3)}$. For simplicity, superscripts on variables are omitted in all figures, as it is self-evident which variable is referenced in each case. This paper presents data flow diagrams in a left-to-right orientation, where straightforward lines within the illustrations represent data transfer operations. Circles in these diagrams represent multiplication operations, with the respective numerical factors inscribed inside. Points of convergence, marked with a bold dot, indicate summation. Additionally, dashed lines indicate data transfer operations with a simultaneous sign change. To maintain visual clarity, standard lines without arrows are employed.



Figure 1. Data flow diagram of the algorithm (5) for N = 3.

3.2. Algorithm for N = 4

Let it be necessary to calculate the matrix-vector product of the following form:

$$\begin{vmatrix} y_0 \\ y_1 \\ y_2 \\ y_3 \end{vmatrix} = \begin{vmatrix} t_3 & t_2 & t_1 & t_0 \\ t_4 & t_3 & t_2 & t_1 \\ t_5 & t_4 & t_3 & t_2 \\ t_6 & t_5 & t_4 & t_3 \end{vmatrix} \begin{vmatrix} x_0 \\ x_1 \\ x_2 \\ x_3 \end{vmatrix}.$$
(6)

The direct method of calculating this product requires 16 multiplications and 12 additions.

Proposition 2. To calculate the product (6), no more than 9 multiplications are required.

Proof. Let us introduce some auxiliary matrices, pre- and postaddition matrices:

 $\mathbf{T}_{6\times4}^{(4)} = \begin{bmatrix} & 1 & & \\ & & 1 & & \\ 1 & 1 & & 1 \\ 1 & & 1 & \\ 1 & & & \\ & 1 & & \end{bmatrix},$

and a diagonal matrix of multiplication factors $\mathbf{D}_{9}^{(4)}$, in which the entries are the algebraic sums of entries of the Toeplitz matrix \mathbf{T}_{4} :

$$\mathbf{D}_{9}^{(4)} = \operatorname{diag}\left(s_{0}^{(4)}, s_{1}^{(4)}, \dots, s_{8}^{(4)}\right),$$

$$s_{0}^{(4)} = w_{0}^{(4)} + w_{1}^{(4)}, \quad s_{1}^{(4)} = -w_{0}^{(4)},$$

$$s_{2}^{(4)} = t_{0} - t_{2} + w_{0}^{(4)}, \quad s_{3}^{(4)} = t_{2} - t_{3}, \quad s_{4}^{(4)} = t_{3},$$

$$s_{5}^{(4)} = t_{4} - t_{3}, \quad s_{6}^{(4)} = -t_{4} + t_{6} + w_{2}^{(4)}, \quad s_{7}^{(4)} = -w_{2}^{(4)},$$

$$s_{8}^{(4)} = -w_{1}^{(4)} + w_{2}^{(4)},$$

$$s_{8}^{(4)} = -w_{1}^{(4)} + w_{2}^{(4)},$$

$$(7)$$

where

$$w_0^{(4)} = -t_1 + t_3, \quad w_1^{(4)} = t_2 - t_4, \quad w_2^{(4)} = t_3 - t_5,$$

and the sign \otimes'' denotes the Kronecker product [49].

Considering the matrices that have been introduced, expression (6) can be represented as follows:

$$\mathbf{Y}_{4\times1} = \mathbf{P}_{4\times6}^{(4)} \mathbf{P}_{6\times9}^{(4)} \mathbf{D}_{9}^{(4)} \mathbf{T}_{9\times6}^{(4)} \mathbf{T}_{6\times4}^{(4)} \mathbf{X}_{4\times1}, \tag{8}$$

where

$$\mathbf{X}_{4 \times 1} = [x_0, x_1, x_2, x_3]^T,$$

 $\mathbf{Y}_{4 \times 1} = [y_0, y_1, y_2, y_3]^T.$

It is easy to see that the multiplicative complexity of expression (8) is 9. The correctness of expression (8) is confirmed by the truth of the following expression:

$$\mathbf{\Gamma}_4 = \mathbf{P}_{4\times 6}^{(4)} \mathbf{P}_{6\times 9}^{(4)} \mathbf{D}_9^{(4)} \mathbf{T}_{9\times 6}^{(4)} \mathbf{T}_{6\times 4'}^{(4)}$$

where T_4 is a 4×4 Toeplitz matrix (1). Expression (8) defines a reduced multiplicative complexity algorithm for calculating the matrix–vector product with a fourth-order Toeplitz matrix. \Box

Remark 2. The proposed algorithm requires only 9 multiplications and 26 additions. This gives, relative to the direct method, a reduction of 7 multiplications at the cost of an additional 14 additions. Suppose the entries of the matrix $\mathbf{D}_{9}^{(4)}$ (7) are constant values that can be precomputed and stored in the memory of a calculator. In that case, the implementation of the algorithm can be accomplished with only 15 additions, significantly reducing the computational requirements. Finally, we obtain a reduction in multiplications by 7 at the cost of 3 extra additions.

Figure 2 shows a data flow diagram of the proposed algorithm.

421



Figure 2. Data flow diagram of the algorithm (8) for N = 4.

3.3. Algorithm for N = 5

Let it be necessary to calculate the matrix-vector product of the following form:

$$\begin{bmatrix} y_0 \\ y_1 \\ y_2 \\ y_3 \\ y_4 \end{bmatrix} = \begin{bmatrix} t_4 & t_3 & t_2 & t_1 & t_0 \\ t_5 & t_4 & t_3 & t_2 & t_1 \\ t_6 & t_5 & t_4 & t_3 & t_2 \\ t_7 & t_6 & t_5 & t_4 & t_3 \\ t_8 & t_7 & t_6 & t_5 & t_4 \end{bmatrix} \begin{bmatrix} x_0 \\ x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix}.$$
(9)

The direct method of calculating this product requires 25 multiplications and 20 additions.

Proposition 3. To calculate the product (9), no more than 14 multiplications are required.

Proof. Let us introduce some auxiliary matrices, pre- and postaddition matrices:

and a diagonal matrix of multiplication factors:

$$\mathbf{D}_{14}^{(5)} = \operatorname{diag}\left(s_{0}^{(5)}, s_{1}^{(5)}, \dots, s_{13}^{(5)}\right), \tag{10}$$

$$s_{0}^{(5)} = -t_{4} - t_{7} + t_{8} + w_{3}^{(5)}, s_{1}^{(5)} = t_{4}, s_{2}^{(5)} = t_{6}, \qquad s_{3}^{(5)} = t_{7}, s_{4}^{(5)} = w_{0}^{(5)}, s_{5}^{(5)} = t_{3}, s_{6}^{(5)} = w_{2}^{(5)}, \qquad s_{7}^{(5)} = t_{6} - t_{5} - t_{4} + t_{3} - t_{7}, s_{8}^{(5)} = t_{5} - t_{3}, \qquad s_{9}^{(5)} = t_{4} - w_{2}^{(5)} + w_{3}^{(5)}, s_{10}^{(5)} = t_{2} - t_{5} + w_{1}^{(5)}, \qquad s_{11}^{(5)} = t_{1} - t_{3}, s_{12}^{(5)} = t_{0} - t_{2} + w_{1}^{(5)}, \qquad s_{13}^{(5)} = t_{5}, \qquad$$

$$w_0^{(5)} = -t_3 + t_4, \quad w_1^{(5)} = -t_1 - w_0^{(5)}, \quad w_2^{(5)} = t_2 - t_3$$

 $w_3^{(5)} = -t_5 - t_6,$

and the sign \oplus ["] denotes the direct sum of matrices [50].

Considering the matrix constructions introduced earlier, expression (9) can be reformulated as follows:

$$\mathbf{Y}_{5\times 1} = \mathbf{P}_{5\times 11}^{(5)} \mathbf{P}_{11\times 14}^{(5)} \mathbf{D}_{14}^{(5)} \mathbf{T}_{14\times 11}^{(5)} \mathbf{T}_{11\times 5}^{(5)} \mathbf{X}_{5\times 1}, \tag{11}$$

where

It is easy to see that the multiplicative complexity of computing expression (11) is 14. The correctness of expression (11) is confirmed by the truth of the following expression:

$$\mathbf{T}_{5} = \mathbf{P}_{5 \times 11}^{(5)} \mathbf{P}_{11 \times 14}^{(5)} \mathbf{D}_{14}^{(5)} \mathbf{T}_{14 \times 11}^{(5)} \mathbf{T}_{11 \times 5'}^{(5)}$$

where T_5 is a 5 × 5 Toeplitz matrix. Expression (11) defines a reduced multiplicative complexity algorithm for calculating the matrix–vector product with a fifth-order Toeplitz matrix. \Box

Remark 3. The proposed algorithm requires only 14 multiplications and 45 additions. This gives, relative to the direct method, a reduction of 11 multiplications at the cost of an additional 25 additions. When the entries of the matrix $\mathbf{D}_{14}^{(5)}$ (10) are constant numbers that can be precalculated and stored in the calculator's memory, the implementation of the algorithm (11) requires only 27 additions, effectively reducing the computational complexity. Finally, we obtain a reduction in multiplications by 11 at the cost of 7 extra additions.

Figure 3 shows a data flow diagram of the proposed algorithm.



Figure 3. Data flow diagram of the algorithm (11) for N = 5.

3.4. Algorithm for N = 6

Let it be necessary to calculate the matrix-vector product of the following form:

$$\begin{bmatrix} y_{0} \\ y_{1} \\ y_{2} \\ y_{3} \\ y_{4} \\ y_{5} \end{bmatrix} = \begin{bmatrix} t_{5} & t_{4} & t_{3} & t_{2} & t_{1} & t_{0} \\ t_{6} & t_{5} & t_{4} & t_{3} & t_{2} & t_{1} \\ t_{7} & t_{6} & t_{5} & t_{4} & t_{3} & t_{2} \\ t_{8} & t_{7} & t_{6} & t_{5} & t_{4} & t_{3} \\ t_{9} & t_{8} & t_{7} & t_{6} & t_{5} & t_{4} \\ t_{10} & t_{9} & t_{8} & t_{7} & t_{6} & t_{5} \end{bmatrix} \begin{bmatrix} x_{0} \\ x_{1} \\ x_{2} \\ x_{3} \\ x_{4} \\ x_{5} \end{bmatrix}.$$
(12)

The direct method of calculating this product requires 36 multiplications and 30 additions. **Proposition 4.** *To calculate the product (12), no more than 18 multiplications are required.*

Proof. Let us introduce auxiliary matrices:

$$\mathbf{P}_{6\times9}^{(6)} = \begin{bmatrix} \mathbf{0}_3 & \mathbf{I}_3 & \mathbf{I}_3 \\ \mathbf{I}_3 & \mathbf{I}_3 & \mathbf{0}_3 \end{bmatrix}, \quad \mathbf{P}_{9\times18}^{(6)} = \mathbf{I}_3 \otimes \mathbf{P}_{3\times6'}^{(3)}$$

 (\mathbf{n})

 (α)

and

where

$$\begin{split} w_0^{(6)} &= -t_5 + t_8, \quad w_1^{(6)} = t_6 - t_7, \\ w_2^{(6)} &= -t_9 + w_1^{(6)}, \quad w_3^{(6)} = t_5 + w_1^{(6)}, \quad w_4^{(6)} = t_3 - t_4, \\ w_5^{(6)} &= t_5 + w_4^{(6)}, \quad w_6^{(6)} = t_2 - t_5. \end{split}$$

Taking into account the introduced matrix constructions, expression (12) can be written in the following form:

$$\mathbf{Y}_{6\times 1} = \mathbf{P}_{6\times 9}^{(6)} \mathbf{P}_{9\times 18}^{(6)} \mathbf{D}_{18}^{(6)} \mathbf{T}_{18\times 9}^{(6)} \mathbf{T}_{9\times 6}^{(6)} \mathbf{X}_{6\times 1}, \tag{14}$$

where

$$\mathbf{X}_{6\times 1} = [x_0, x_1, x_2, x_3, x_4, x_5]^T, \mathbf{Y}_{6\times 1} = [y_0, y_2, y_3, y_3, y_4, y_5]^T.$$

It is easy to see that the multiplicative complexity of calculating expression (14) is 18.

 $\mathbf{X}_{6\times 1} = [x_0, .$

The correctness of expression (14) can be checked by a simple substitution:

$$\mathbf{T}_6 = \mathbf{P}_{6\times 9}^{(6)} \mathbf{P}_{9\times 18}^{(6)} \mathbf{D}_{18}^{(6)} \mathbf{T}_{18\times 9}^{(6)} \mathbf{T}_{9\times 6}^{(6)}$$

where T_6 is a 6 × 6 Toeplitz matrix. Expression (14) defines a reduced multiplicative complexity algorithm for calculating the matrix–vector product with a sixth-order Toeplitz matrix. \Box

Remark 4. The proposed algorithm (14) requires only 18 multiplications and 75 additions. Suppose the entries of the matrix $\mathbf{D}_{18}^{(6)}$ (13) are constant values that can be precomputed and stored in the memory of a calculator. In that case, the implementation of the algorithm can be accomplished with only 33 additions, significantly reducing the computational requirements. Thus, the proposed algorithm (14) applied to the calculation of the matrix–vector product (12) reduces 18 multiplications at the expense of 3 extra additions compared to the direct method.



Figure 4 shows a data flow diagram of the proposed algorithm.

Figure 4. Data flow diagram of the algorithm (14) for N = 6.

3.5. Algorithm for N = 7

Let it be necessary to calculate the matrix-vector product of the following form:

$$\begin{bmatrix} y_{0} \\ y_{1} \\ y_{2} \\ y_{3} \\ y_{4} \\ y_{5} \\ y_{6} \end{bmatrix} = \begin{bmatrix} t_{6} & t_{5} & t_{4} & t_{3} & t_{2} & t_{1} & t_{0} \\ t_{7} & t_{6} & t_{5} & t_{4} & t_{3} & t_{2} & t_{1} \\ t_{8} & t_{7} & t_{6} & t_{5} & t_{4} & t_{3} & t_{2} \\ t_{9} & t_{8} & t_{7} & t_{6} & t_{5} & t_{4} & t_{3} \\ t_{10} & t_{9} & t_{8} & t_{7} & t_{6} & t_{5} & t_{4} \\ t_{11} & t_{10} & t_{9} & t_{8} & t_{7} & t_{6} & t_{5} \\ t_{12} & t_{11} & t_{10} & t_{9} & t_{8} & t_{7} & t_{6} \end{bmatrix} \begin{bmatrix} x_{0} \\ x_{1} \\ x_{2} \\ x_{3} \\ x_{4} \\ x_{5} \\ x_{6} \end{bmatrix}.$$
(15)

The direct method of calculating this product requires 49 multiplications and 42 additions.

Proposition 5. To calculate the product (15), no more than 25 multiplications are required.

Proof. Let us introduce auxiliary matrices:

$$P_{16\times 25}^{(7)} = I_4 \oplus P_{3\times 6}^{(3)} \oplus I_2 \oplus P_{3\times 6}^{(3)} \oplus 1 \oplus P_{3\times 6}^{(3)}$$

and

$$w_0^{(7)} = -t_7 - t_8 - t_9 - t_{11}, \quad w_1^{(7)} = t_5 + t_6,$$

 $w_2^{(7)} = -t_3 + t_4, \quad w_3^{(7)} = -t_8 - s_5^{(7)} + w_2^{(7)}$

Taking into account the introduced matrix constructions, expression (3) can be written in the following form:

$$\mathbf{Y}_{7\times1} = \mathbf{P}_{7\times16}^{(7)} \mathbf{P}_{16\times25}^{(7)} \mathbf{D}_{25}^{(7)} \mathbf{T}_{25\times16}^{(7)} \mathbf{T}_{16\times7}^{(7)} \mathbf{X}_{7\times1}$$
(17)

(16)

$$\mathbf{X}_{7 \times 1} = [x_0, x_1, x_2, x_3, x_4, x_5, x_6]^T \\ \mathbf{Y}_{7 \times 1} = [y_0, y_2, y_3, y_3, y_4, y_5, y_6]^T$$

It is easy to see that the multiplicative complexity of calculating expression (17) is 25. The correctness of expression (17) can be checked by a simple substitution:

$$\mathbf{T}_{7} = \mathbf{P}_{7 \times 16}^{(7)} \mathbf{P}_{16 \times 25}^{(7)} \mathbf{D}_{25}^{(7)} \mathbf{T}_{25 \times 16}^{(7)} \mathbf{T}_{16 \times 74}^{(7)}$$

where T_7 is a 7 × 7 Toeplitz matrix. Expression (17) defines a reduced multiplicative complexity algorithm for calculating the matrix–vector product with a seventh-order Toeplitz matrix.

Remark 5. The proposed algorithm (17) requires only 25 multiplications and 87 additions. When the entries of the matrix $\mathbf{D}_{25}^{(7)}$ (16) are constant numbers that can be precalculated and stored in the calculator's memory, the implementation of the algorithm (17) requires only 51 additions, effectively reducing the computational complexity. Finally, we obtain a reduction in multiplications by 24 at the cost of 9 extra additions.

Figure 5 shows a data flow diagram of the proposed algorithm.



Figure 5. Data flow diagram of the algorithm (17) for N = 7.

3.6. Algorithm for N = 8

Let it be necessary to calculate the matrix-vector product of the following form:

$$\begin{bmatrix} y_{0} \\ y_{1} \\ y_{2} \\ y_{3} \\ y_{4} \\ y_{5} \\ y_{6} \\ y_{7} \end{bmatrix} = \begin{bmatrix} t_{7} & t_{6} & t_{5} & t_{4} & t_{3} & t_{2} & t_{1} & t_{0} \\ t_{8} & t_{7} & t_{6} & t_{5} & t_{4} & t_{3} & t_{2} & t_{1} \\ t_{9} & t_{8} & t_{7} & t_{6} & t_{5} & t_{4} & t_{3} & t_{2} \\ t_{10} & t_{9} & t_{8} & t_{7} & t_{6} & t_{5} & t_{4} & t_{3} \\ t_{11} & t_{10} & t_{9} & t_{8} & t_{7} & t_{6} & t_{5} & t_{4} \\ t_{12} & t_{11} & t_{10} & t_{9} & t_{8} & t_{7} & t_{6} & t_{5} \\ t_{13} & t_{12} & t_{11} & t_{10} & t_{9} & t_{8} & t_{7} & t_{6} \\ t_{14} & t_{13} & t_{12} & t_{11} & t_{10} & t_{9} & t_{8} & t_{7} \end{bmatrix} \begin{bmatrix} x_{0} \\ x_{1} \\ x_{2} \\ x_{3} \\ x_{4} \\ x_{5} \\ x_{6} \\ x_{7} \end{bmatrix}.$$
(18)

The direct method of calculating this product requires 64 multiplications and 56 additions.

Proposition 6. To calculate the product (18), no more than 27 multiplications are required.

Proof. Let us introduce auxiliary matrices:

$$\mathbf{P}_{8\times12}^{(8)} = \mathbf{P}_{2\times3}^{(4)} \otimes \mathbf{I}_4, \quad \mathbf{P}_{12\times18}^{(8)} = \mathbf{I}_3 \otimes \mathbf{P}_{4\times6'}^{(8)}$$
$$\mathbf{P}_{4\times6}^{(8)} = \mathbf{P}_{2\times3}^{(4)} \otimes \mathbf{I}_2, \quad \mathbf{P}_{18\times27}^{(8)} = \mathbf{I}_9 \otimes \mathbf{P}_{2\times3'}^{(4)}$$

and

$$\begin{split} \mathbf{T}_{27\times18}^{(8)} &= \mathbf{I}_9 \otimes \mathbf{T}_{3\times2}^{(4)}, \ \mathbf{T}_{18\times12}^{(8)} &= \mathbf{I}_3 \otimes \mathbf{T}_{6\times4}^{(8)}, \\ \mathbf{T}_{6\times4}^{(8)} &= \mathbf{T}_{3\times2}^{(4)} \otimes \mathbf{I}_2, \\ \\ \mathbf{T}_{12\times8}^{(8)} &= \begin{bmatrix} & 1 \\$$

$$\begin{split} s_{17}^{(8)} &= t_7 - t_8 + w_6^{(8)}, \quad s_{18}^{(8)} = -t_4 + t_6 - t_{10} + w_5^{(8)} + w_7^{(8)}, \\ s_{19}^{(8)} &= t_9 - w_7^{(8)}, \quad s_{20}^{(8)} = -s_{11}^{(8)} + w_6^{(8)} + w_8^{(8)}, \\ s_{21}^{(8)} &= t_{10} - t_{11} - s_{12}^{(8)}, \quad s_{22}^{(8)} = t_{11} - t_7, \\ s_{23}^{(8)} &= -s_{14}^{(8)} - w_8^{(8)}, \quad s_{24}^{(8)} = t_{12} - t_{13} - s_{21}^{(8)} - w_5^{(8)}, \\ s_{25}^{(8)} &= -t_{11} + t_{13} - s_{16}^{(8)}, \\ s_{26}^{(8)} &= -t_{13} + t_{14} + s_{14}^{(8)} - w_6^{(8)} + w_8^{(8)}, \end{split}$$

$$\begin{split} w_0^{(8)} &= -t_1 + t_3 - t_4 + s_{10}^{(8)}, \quad w_1^{(8)} = t_2 - t_6, \\ w_2^{(8)} &= t_4 - t_8, \quad w_3^{(8)} = -t_5 + t_9, \quad w_4^{(8)} = t_6 + w_3^{(8)}, \\ w_5^{(8)} &= t_8 - t_9, \quad w_6^{(8)} = -t_9 + t_{10}, \quad w_7^{(8)} = t_{11} + s_{10}^{(8)}, \\ w_8^{(8)} &= t_{11} - t_{12}. \end{split}$$

Taking into account the introduced matrix constructions, expression (18) can be written in the following form:

$$\mathbf{Y}_{8\times1} = \mathbf{P}_{8\times12}^{(8)} \mathbf{P}_{12\times18}^{(8)} \mathbf{P}_{18\times27}^{(8)} \mathbf{D}_{27}^{(8)} \mathbf{T}_{27\times18}^{(8)} \mathbf{T}_{18\times12}^{(8)} \mathbf{T}_{12\times8}^{(8)} \mathbf{X}_{8\times1},$$
(20)

where

$$\mathbf{X}_{8\times 1} = [x_0, x_1, x_2, x_3, x_4, x_5, x_6, x_7]^T, \mathbf{Y}_{8\times 1} = [y_0, y_2, y_3, y_3, y_4, y_5, y_6, y_7]^T.$$

It is easy to see that the multiplicative complexity of calculating expression (20) is 27. The correctness of expression (20) can be checked by a simple substitution:

$$\mathbf{T}_8 = \mathbf{P}_{8 \times 12}^{(8)} \mathbf{P}_{12 \times 18}^{(8)} \mathbf{P}_{18 \times 27}^{(8)} \mathbf{D}_{27}^{(8)} \mathbf{T}_{27 \times 18}^{(8)} \mathbf{T}_{18 \times 12}^{(8)} \mathbf{T}_{12 \times 8}^{(8)}$$

where T_8 is an 8 × 8 Toeplitz matrix. Expression (20) defines a reduced multiplicative complexity algorithm for calculating the matrix–vector product with an eighth-order Toeplitz matrix. \Box

Remark 6. The proposed algorithm (20) requires only 27 multiplications and 114 additions. Suppose the entries of the matrix $\mathbf{D}_{27}^{(8)}$ (19) are constant values that can be precomputed and stored in the memory of a calculator. In that case, the implementation of the algorithm can be accomplished with only 57 additions, significantly reducing the computational requirements. Finally, we obtain a reduction in multiplications by 37 at the cost of one extra addition compared to the direct method.

Figure 6 shows a data flow diagram of the proposed algorithm.



Figure 6. Data flow diagram of the algorithm (20) for N = 8.

3.7. Algorithm for N = 9

Let it be necessary to calculate the matrix-vector product of the following form:

$$\begin{vmatrix} y_0 \\ y_1 \\ y_2 \\ y_3 \\ y_4 \\ y_5 \\ y_6 \\ y_7 \\ y_8 \end{vmatrix} = \begin{vmatrix} t_8 & t_7 & t_6 & t_5 & t_4 & t_3 & t_2 & t_1 & t_0 \\ t_9 & t_8 & t_7 & t_6 & t_5 & t_4 & t_3 & t_2 & t_1 \\ t_{10} & t_9 & t_8 & t_7 & t_6 & t_5 & t_4 & t_3 & t_2 \\ t_{11} & t_{10} & t_9 & t_8 & t_7 & t_6 & t_5 & t_4 & t_3 \\ t_{12} & t_{11} & t_{10} & t_9 & t_8 & t_7 & t_6 & t_5 & t_4 \\ t_{13} & t_{12} & t_{11} & t_{10} & t_9 & t_8 & t_7 & t_6 & t_5 \\ t_{14} & t_{13} & t_{12} & t_{11} & t_{10} & t_9 & t_8 & t_7 & t_6 \\ t_{15} & t_{14} & t_{13} & t_{12} & t_{11} & t_{10} & t_9 & t_8 & t_7 \\ t_{16} & t_{15} & t_{14} & t_{14} & t_{12} & t_{11} & t_{10} & t_9 & t_8 \\ t_{15} & t_{14} & t_{14} & t_{12} & t_{11} & t_{10} & t_9 & t_8 \\ t_{15} & t_{14} & t_{13} & t_{12} & t_{11} & t_{10} & t_9 & t_8 & t_7 \\ t_{16} & t_{15} & t_{14} & t_{14} & t_{12} & t_{11} & t_{11} & t_9 & t_8 \\ \end{vmatrix}$$

The direct method of calculating this product requires 81 multiplications and 72 additions.

Proposition 7. To calculate the product (21), no more than 36 multiplications are required.

Proof. Let us introduce auxiliary matrices:

$$\begin{split} \mathbf{P}_{18\times 36}^{(9)} &= \mathbf{I}_6 \otimes \mathbf{P}_{3\times 6\prime}^{(9)}, \\ \mathbf{P}_{3\times 6}^{(9)} &= \begin{bmatrix} 1 & & 1 & 1 \\ & 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}, \end{split}$$

and

$$\mathbf{D}_{36}^{(9)} = \operatorname{diag}\left(s_{0}^{(9)}, s_{1}^{(9)}, \dots, s_{35}^{(9)}\right),$$

$$s_{0}^{(9)} = t_{8}, \quad s_{1}^{(9)} = -t_{8} - w_{0}^{(9)}, \quad s_{2}^{(9)} = t_{9},$$

$$s_{3}^{(9)} = -t_{7} + t_{8} - t_{9}, \quad s_{4}^{(9)} = t_{7}, \quad s_{5}^{(9)} = -t_{8} + w_{1}^{(9)},$$

$$s_{6}^{(9)} = t_{11}, \quad s_{7}^{(9)} = -t_{11} - w_{2}^{(9)}, \quad s_{8}^{(9)} = t_{12},$$

$$s_{9}^{(9)} = -t_{10} + t_{11} - t_{12}, \quad s_{10}^{(9)} = t_{10},$$

$$s_{11}^{(9)} = -t_{11} + w_{0}^{(9)}, \quad s_{12}^{(9)} = -t_{11} + t_{14} - t_{8},$$

(22)

$$\begin{split} s_{13}^{(9)} &= -t_{15} + t_{16} - s_1^{(9)} + w_3^{(9)}, \quad s_{14}^{(9)} = -t_{12} + t_{15} - t_9, \\ s_{15}^{(9)} &= -t_{13} + t_{14} - t_{15} - s_3^{(9)} - s_9^{(9)}, \\ s_{16}^{(9)} &= -t_{10} + t_{13} - t_7, \quad s_{17}^{(9)} = -w_0^{(9)} - s_5^{(9)} + w_3^{(9)}, \\ s_{18}^{(9)} &= t_8 - w_4^{(9)}, \quad s_{19}^{(9)} = -w_0^{(9)} + s_5^{(9)} + w_2^{(9)} + w_4^{(9)}, \\ s_{20}^{(9)} &= -t_6 + t_9 - t_{12}, \quad s_{27}^{(9)} = t_5 - t_4 - t_6, \\ s_{21}^{(9)} &= s_3^{(9)} - s_9^{(9)} - s_{27}^{(9)}, \quad s_{22}^{(9)} = -t_4 + t_7 - t_{10}, \\ s_{23}^{(9)} &= -w_0^{(9)} + s_5^{(9)} + w_4^{(9)} - w_5^{(9)}, \quad s_{24}^{(9)} = t_5, \\ s_{25}^{(9)} &= -t_5 - t_6 + t_7, \quad s_{26}^{(9)} = t_6, \quad s_{28}^{(9)} = t_4, \\ s_{29}^{(9)} &= -t_5 + w_5^{(9)}, \quad s_{30}^{(9)} = -t_8 - w_6^{(9)}, \\ s_{31}^{(9)} &= -s_1^{(9)} + w_1^{(9)} - w_5^{(9)} + w_6^{(9)}, \quad s_{32}^{(9)} = t_3 - t_6 - t_9, \\ s_{33}^{(9)} &= t_2 - s_3^{(9)} - s_{27}^{(9)} + w_7^{(9)}, \quad s_{34}^{(9)} = t_1 - t_4 - t_7, \\ s_{35}^{(9)} &= t_0 + t_4 - s_5^{(9)} + w_6^{(9)} + w_7^{(9)}, \end{split}$$

$$w_0^{(9)} = t_9 - t_{10}, \quad w_1^{(9)} = t_6 - t_7, \quad w_2^{(9)} = t_{12} - t_{13},$$

$$w_3^{(9)} = -t_{14} - s_7^{(9)}, \quad w_4^{(9)} = t_5 + t_{11}, \quad w_5^{(9)} = t_3 - t_4$$

$$w_6^{(9)} = -t_2 + t_5, \quad w_7^{(9)} = -t_1 - t_3.$$

Taking into account the introduced matrix constructions, expression (21) can be written in the following form:

$$\mathbf{Y}_{9\times 1} = \mathbf{P}_{9\times 18}^{(9)} \mathbf{P}_{18\times 36}^{(9)} \mathbf{D}_{36}^{(9)} \mathbf{T}_{36\times 18}^{(9)} \mathbf{T}_{18\times 9}^{(9)} \mathbf{X}_{9\times 1},$$
(23)

where

$$\mathbf{X}_{9\times1} = [x_0, x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8]^T, \\ \mathbf{Y}_{9\times1} = [y_0, y_2, y_3, y_3, y_4, y_5, y_6, y_7, y_8]^T.$$

It is easy to see that the multiplicative complexity of calculating expression (23) is 36. The correctness of expression (23) can be checked by a simple substitution:

$$\mathbf{T}_9 = \mathbf{P}_{9\times 18}^{(9)} \mathbf{P}_{18\times 36}^{(9)} \mathbf{D}_{36}^{(9)} \mathbf{T}_{36\times 18}^{(9)} \mathbf{T}_{18\times 9}^{(9)},$$

where T_9 is a Toeplitz matrix (1) of the 9th order. Expression (5) defines a reduced multiplicative complexity algorithm for calculating the matrix–vector product with a ninth-order Toeplitz matrix.

Remark 7. The proposed algorithm (5) requires only 36 multiplications and 144 additions. In a number of practical applications, the entries of the Toeplitz matrix are constant numbers. Then the entries of the matrix $\mathbf{D}_{36}^{(9)}(22)$, i.e., t_0, t_1, \ldots, t_{16} , can be calculated in advance and stored in the calculator's memory. For this case, the number of additions in the algorithm is reduced to 81. Thus, the proposed algorithm (23) applied to the calculation of the matrix–vector product (21) reduces 45 multiplications at the expense of 9 extra additions, compared to the direct method.

Figure 7 shows a data flow diagram of the proposed algorithm.



Figure 7. Data flow diagram of the algorithm (23) for N = 9.

4. Computational Cost Analysis

Compared to the direct method, the proposed algorithms achieve a notable reduction in the number of multiplications at the expense of an increase in elementary additions. Table 1 summarizes this reduction. As multiplication operations typically require more resources than additions, the proposed method offers resource savings in applicationspecific integrated circuits (ASICs) and enables the use of more straightforward and cheaper field-programmable gate arrays (FPGAs).

The number of additions is reduced when constant coefficient values are present in the Toeplitz matrix. In such a situation, it becomes possible to precalculate the multipliers appearing in matrices $\mathbf{D}_{6}^{(3)}(4)$, $\mathbf{D}_{9}^{(4)}(7)$, $\mathbf{D}_{14}^{(5)}(10)$, $\mathbf{D}_{18}^{(6)}(13)$, $\mathbf{D}_{25}^{(7)}(16)$, $\mathbf{D}_{27}^{(8)}(19)$, or $\mathbf{D}_{36}^{(9)}(22)$. As a result, there is a notable reduction in the number of additions, as included in Table 2.

Order of	Multiplications			A	Additions			Arithmetic Operation	
Matrix	Direct	Prop.	Reduct.	Direct	Prop.	Incr.	Direct	Prop.	Incr.
3	9	6	3	6	15	9	15	21	6
4	16	9	7	12	26	14	28	35	7
5	25	14	11	20	45	25	45	59	14
6	36	18	18	30	60	30	66	78	12
7	49	25	24	42	87	45	91	112	21
8	64	27	37	56	114	58	120	141	21
9	81	36	45	72	144	72	153	180	27

Table 1. The comparison of the number of multiplications and additions in the direct method and the proposed algorithm in the general case.

Table 2. The comparison of the number of multiplications and additions in the direct method and the proposed algorithm, assuming a constant value of the elements of the Toeplitz matrix.

Order of	er of Multiplications			Additions			Arithmetic Operations		
Matrix	Direct	Prop.	Reduct.	Direct	Prop.	Incr.	Direct	Prop.	Reduct.
3	9	6	3	6	9	3	15	15	0
4	16	9	7	12	15	3	28	24	4
5	25	14	11	20	27	7	45	41	4
6	36	18	18	30	33	3	66	51	15
7	49	25	24	42	51	9	91	76	15
8	64	27	37	56	57	1	120	84	36
9	81	36	45	72	81	9	153	117	36

The proposed algorithm was exemplified in FPGAs on Xilinx's Spartan 3, the most straightforward possible device of the Spartan series, containing the number of inputs and outputs required by the algorithm. The 8-bit x_i inputs, 16-bit y_i outputs, and fixed 8-bit coefficients in the Toeplitz matrix were assumed. Table 3 shows the number of slices and Table 4 the four-input LUTs used in the Spartan 3 FPGA implementation. Both algorithms took full advantage of the available multipliers MULT 18 × 18 on each FPGA chip, as shown in Table 3. A significant reduction in the logic blocks used was achieved in the example applications shown.

Table 3. The number of available multipliers and used slices in implementations of algorithms on Spartan 3 FPGAs.

Order of Matrix	Devices	MULT 18 $ imes$ 18	Direct	Slices Proposed	Reduction
3	xc3s50-4pq208	4	136	76	44.1%
4	xc3s50-4pq208	4	292	210	28.1%
5	xc3s200-4pq208	12	384	249	35.2%
6	xc3s400-4fg456	16	542	332	38.7%
7	xc3s400-4fg456	16	934	634	32.1%
8	xc3s1000-4fg456	24	1011	553	45.3%
9	xc3s1000-4fg676	24	1519	890	41.4%

Order of			4 Input LUTs	
Matrix	Devices	Direct	Proposed	Reduction
3	xc3s50-4pq208	256	140	45.3%
4	xc3s50-4pq208	549	382	30.4%
5	xc3s200-4pq208	729	467	35.9%
6	xc3s400-4fg456	1031	612	40.6%
7	xc3s400-4fg456	1757	1172	33.3%
8	xc3s1000-4fg456	1871	1042	44.3%
9	xc3s1000-4fg676	2882	1656	42.5%

Table 4. The number of 4-input LUTs used in implementations of algorithms on Spartan 3 FPGAs.

5. Conclusions

In this paper, we proposed the algorithms for calculating matrix–vector products with Toeplitz matrices with order *N* equal to 3, 4, 5, 6, 7, 8, and 9. The algorithms we proposed aim to decrease the number of multiplications, albeit at the cost of additional additions compared to the direct algorithm. This trade-off is advantageous due to the additions' relatively lower resource requirements compared with multiplications.

Further reduction can be achieved when the entries in the Toeplitz matrix are constants. In such instances, a preprocessing step allows certain additions to be performed outside the algorithm. This approach effectively reduces the number of additions required during the algorithm's execution. Consequently, the overall count of arithmetic operations is lower than the conventional direct method.

Author Contributions: Conceptualization, A.C.; methodology, A.C., J.P.P., and P.S.; formal analysis, A.C., J.P.P., P.S. and M.M.; writing—original draft preparation, J.P.P.; writing—review and editing, A.C. and J.P.P.; visualization, A.C., J.P.P., P.S. and M.M.; supervision, A.C. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: Dataset available on request from the authors.

Acknowledgments: We would like to thank the esteemed reviewers for their efforts and assistance in improving the quality of our manuscript.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

FFT fast Fourier transform

References

- 1. Eidelman, Y.; Gohberg, I.; Haimovici, I. Separable type representations of matrices and fast algorithms. In *Operator Theory: Advances and Applications*; Birkhauser Springer: Basel, Switzerland, 2014; Volume 234.
- 2. Neuts, M.F. Structured Stochastic Matrices of M/G/1 Type and Their Applications; CRC Press: New York, NY, USA, 2021.
- 3. Olshevsky, V. Fast Algorithms for Structured Matrices: Theory and Applications: AMS-IMS-SIAM Joint Summer Research Conference on Fast Algorithms in Mathematics, Computer Science, and Engineering, 5–9 August 2001, Mount Holyoke College, South Hadley, Massachusetts; Contemporary Mathematics; American Mathematical Soc.: South Hadley, MA, USA, 2003; Volume 323.
- 4. Pan, V. Structured Matrices and Polynomials: Unified Superfast Algorithms; Springer Science & Business Media: Boston, MA, USA, 2001.
- Yagle, A.E. 22 fast algorithms for structured matrices in signal processing. In *Handbook of Statist*; Elsevier: Amsterdam, The Netherlands, 1993; Volume 10, pp. 933–972. [CrossRef]
- Strang, G. The discrete cosine transform, block Toeplitz matrices, and wavelets. In *Advances in Computational Mathematics*; CRC Press: Boca Raton, FL, USA, 1999; Volume 202, pp. 517–536.
- Haupt, J.; Bajwa, W.U.; Raz, G.; Nowak, R. Toeplitz compressed sensing matrices with applicat ions to sparse channel estimation. *IEEE Trans. Inf. Theory* 2010, 56, 5862–5875. [CrossRef]
- 8. Chen, Z.; Nagy, J.G.; Xi, Y.; Yu, B. Structured FISTA for image restoration. Numer. Linear Algebra Appl. 2020, 27, 2278. [CrossRef]

- 9. Hu, Y.; Liu, X.; Jacob, M. A generalized structured low-rank matrix completion algorithm for mr image recovery. *IEEE Trans. Med. Imaging* **2018**, *38*, 1841–1851. [CrossRef]
- 10. Zhang, X.; Zheng, Y.; Jiang, Z.; Byun, H. Numerical algorithms for corner-modified symmetric Toeplitz linear system with applications to image encryption and decryption. *J. Appl. Math. Comput.* **2023**, *69*, 1967–1987. [CrossRef]
- Moir, T. Toeplitz matrices for lti systems, an illustration of their application to wiener filters and estimators. *Internat. J. Syst. Sci.* 2018, 49, 800–817. [CrossRef]
- 12. Zhang, Y.; Zhang, Y.; Li, W.; Huang, Y.; Yang, J. Super-resolution surface mapping for scanning radar: Inverse filtering based on the fast iterative adaptive approach. *IEEE Trans. Geosci. Remote. Sens.* **2017**, *56*, 127–144. [CrossRef]
- 13. Chan, R.H.-F.; Jin, X.-Q. An Introduction to Iterative Toeplitz Solvers; SIAM: Philadelphia, PA, USA , 2007.
- Goian, A.; AlHajri, M.I.; Shubair, R.M.; Weruaga, L.; Kulaib, A.R.; AlMemari, R.; Darweesh, M. Fast detection of coherent signals using pre-conditioned root-music based on Toeplitz matrix reconstruction. In Proceedings of the WiMob 2015: IEEE 11th International Conference on Wireless and Mobile Computing, Networking and Communications, Abu Dhabi, United Arab Emirates, 19–21 October 2015; IEEE: Piscataway, NJ, USA, 2015; pp. 168–174.
- Laskar, M.R.; Mondal, S.; Dutta, A.K. A low complexity quantum simulation framework for Toeplitz-structured matrix and its application in signal processing. *IEEE Trans. Quantum Eng.* 2023, 4, 1–23. [CrossRef]
- Qiao, H.; Pal, P. Generalized nested sampling for compressing low rank Toeplitz matrices. *IEEE Signal Process. Lett.* 2015, 22, 1844–1848. [CrossRef]
- 17. Steimel, U. Fast computation of Toeplitz forms under narrowband conditions with applications to statistical signal processing. *Signal Process.* **1979**, *1*, 141–158. [CrossRef]
- 18. Chen, B.; Liu, Y.; Zhang, C.; Wang, Z. Time series data for equipment reliability analysis with deep learning. *IEEE Access* 2020, *8*, 105484–105493. [CrossRef]
- Albu, F.; Fagan, A. The Gauss-Seidel pseudo affine projection algorithm and its application for echo cancellation. In Proceedings of the Thrity-Seventh Asilomar Conference on Signals, Systems & Computers, Pacific Grove, CA, USA, 9–12 November 2003; IEEE: Piscataway, NJ, USA, 2003; pp. 1303–1306.
- Lu, L.; Yin, K.L.; de Lamare, R.C.; Zheng, Z.; Yu, Y.; Yang, X.; Chen, B. A survey on active noise control in the past decade—Part I: Linear systems. *Signal Process.* 2021, 183, 108039. [CrossRef]
- 21. Wu, L.; Qiu, X.; Guo, Y. A generalized leaky FxLMS algorithm for tuning the waterbed effect of feedback active noise control systems. *Mech. Syst. Signal Process.* **2018**, *106*, 13–23. [CrossRef]
- 22. Pan, J.S.; Lee, C.Y.; Sghaier, A.; Zeghid, M.; Xie, J. Novel systolization of subquadratic space complexity multipliers based on Toeplitz matrix–vector product approach. *IEEE Trans. Very Large Scale Integr. (Vlsi) Syst.* **2019**, 27, 1614–1622. [CrossRef]
- 23. Taşkin, H.K.; Cenk, M. Speeding up curve25519 using Toeplitz matrix-vector multiplication. In Proceedings of the Fifth Workshop on Cryptography and Security in Computing Systems, HiPEAC, Manchester, UK, 22–25 January 2018; pp. 1–6. [CrossRef]
- 24. Ye, G. A chaotic image cryptosystem based on Toeplitz and hankel matrices. Imaging Sci. J. 2009, 57, 266–273. [CrossRef]
- 25. Araujo, A. Building compact and robust deep neural networks with Toeplitz matrices. arXiv 2021, arXiv:2109.00959. [CrossRef]
- Araujo, A.; Negrevergne, B.; Chevaleyre, Y.; Atif, J. On lipschitz regularization of convolutional layers using Toeplitz matrix theory. In Proceedings of the AAAI Conference on Artificial Intelligence, Virtual, 2–9 February 2021; Volume 35, pp. 6661–6669.
- Liao, S.; Samiee, A.; Deng, C.; Bai, Y.; Yuan, B. Compressing deep neural networks using Toeplitz matrix: Algorithm design and fpga implementation. In Proceedings of the ICASSP 2019: IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), Brighton, UK, 12–17 May 2019; IEEE: Piscataway, NJ, USA, 2019; pp. 1443–1447.
- Liu, Y.; Jiao, S.; Lim, L.-H. Lu decomposition and Toeplitz decomposition of a neural network. *Appl. Comput. Harmon. Anal.* 2024, 68, 101601. [CrossRef]
- Lu, Z.; Sindhwani, V.; Sainath, T.N. Learning compact recurrent neural networks. In Proceedings of the ICASSP 2016 IEEE International Conference on Acoustics, Speech and Signal Processing, Shanghai, China, 20–25 March 2016; IEEE: Piscataway, NJ, USA, 2016.
- 30. Wang, J.; Chen, Y.; Chakraborty, R.; Yu, S.X. Orthogonal convolutional neural networks. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, Virtual, 14–19 June 2020; IEEE: Piscataway, NJ, USA, 2020; pp. 11505–11515.
- Wu, X.; Yang, X.; Jia, X.; Tian, F. A gridless DOA estimation method based on convolutional neural network with Toeplitz prior. IEEE Signal Process. Lett. 2022, 29, 1247–1251. [CrossRef]
- 32. Elvander, F.; Jakobsson, A.; Karlsson, J. Interpolation and extrapolation of Toeplitz matrices via optimal mass transport. *IEEE Trans. Signal Process.* 2018, *66*, 5285–5298. [CrossRef]
- Esfandiari, M.; Vorobyov, S.A.; Heath, R.W. Sparsity enforcing with Toeplitz matrix reconstruction method for mmwave ul channel estimation with one-bit adcs. In Proceedings of the 2022 IEEE 12th Sensor Array and Multichannel Signal Processing Workshop (SAM), Trondheim, Norway, 20–23 June 2022; IEEE: Piscataway, NJ, USA, 2022; pp. 141–145.
- Liu, Z.; Wu, N.; Qin, X.; Zhang, Y. Trigonometric transform splitting methods for real symmetric Toeplitz systems. *Comput. Math. Appl.* 2018, 75, 2782–2794. [CrossRef]
- Presti, L.L.; La Cascia, M. Boosting hankel matrices for face emotion recognition and pain detection. *Comput. Vis. Image Underst.* 2017, 156, 19–33. [CrossRef]
- 36. Qi, B.; Liu, X.; Dou, D.; Zhang, Y.; Hu, R. An enhanced doa estimation method for coherent sources via Toeplitz matrix reconstruction and Khatri–Rao subspace. *Electronics* **2023**, *20*, 4268. [CrossRef]

- 37. Saeed, K. Object classification and recognition using Toeplitz matrices. In *Artificial Intelligence and Security in Computing Systems;* Springer: Boston, MA, USA, 2003; pp. 163–172.
- 38. Xu, Z.; Saleh, J.H. Machine learning for reliability engineering and safety applications: Review of current status and future opportunities. *Reliab. Eng. Syst. Saf.* **2021**, *211*, 107530. [CrossRef]
- Jiafeng, X.; Chiou-Yng, L.; Pramod Kumar, M. Low-complexity systolic multiplier for GF (2 m) using Toeplitz matrix-vector product method. In Proceedings of the 2019 IEEE International Symposium on Circuits and Systems (ISCAS), Sapporo, Japan, 26–29 May 2019; IEEE: Piscataway, NJ, USA, 2019; pp. 1–5. [CrossRef]
- 40. Chan, R.H.; Ng, M.K. Conjugate gradient methods for Toeplitz systems. SIAM Rev. 1996, 38, 427–482. [CrossRef]
- 41. Heinig, G.; Rost, K. Fast algorithms for Toeplitz and hankel matrices. Linear Algebra Appl. 2011, 435, 1–59. [CrossRef]
- 42. Hsue, J.-J.; Yagle, A.E. Fast algorithms for solving Toeplitz systems of equations using number-theoretic transforms. *Signal Process*. **1995**, 44, 89–101. [CrossRef]
- 43. Chen, W.W.; Hurvich, C.M.; Lu, Y. On the correlation matrix of the discrete fourier transform and the fast solution of large Toeplitz systems for long-memory time series. *J. Amer. Statist. Assoc.* **2006**, *101*, 812–822. [CrossRef]
- Dongarra, J.; Koev, P.; Li, X. Matrix-vector and matrix-matrix multiplications. In *Templates for the Solution of Algebraic Eigenvalue* Problems: A Practical Guide; SIAM: Philadelphia, PA, USA, 2000; Volume 11, pp. 320–326.
- 45. Cariow, A.; Gliszczyński, M. Fast algorithms to compute matrix-vector products for Toeplitz and hankel matrices. *Electr. Rev.* **2012**, *88*, 166–171.
- 46. Beliakov, G. On fast matrix-vector multiplication with a hankel matrix in multiprecision arithmetics. *arXiv* **2014**, arXiv:1402.5287. [CrossRef]
- 47. Karatsuba, A.A.; Ofman, Y.P. Multiplication of many-digital numbers by automatic computers. *Dokl. Akad. Nauk. Russ. Acad. Sci.* **1962**, 145, 293–294.
- Cariow, A. Strategies for the synthesis of fast algorithms for the computation of the matrix-vector products. J. Signal Process. Theory Appl. 2014, 3, 1–19. [CrossRef]
- 49. Van Loan, C.F. The ubiquitous kronecker product. J. Comput. Appl. Math. 2000, 123, 85–100. [CrossRef]
- 50. Ayres, F. Theory and Problems of Matrices; McGraw-Hill: New York, NY, USA, 1962.

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.