# DETERMINING THE NUMBER OF PROCESSING ELEMENTS IN SYSTOLIC ARRAYS 

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Dedicated to Professor R. Z̆. Djordjević in the occasion of his 65th birthday


#### Abstract

In this paper we determine the minimal number of processing in the 2D systolic implementation for one class of nested loop algorithms. The number of processing elements is derived depending on the projection direction and size of loops. Obtained results are illustrated on matrix multiplication algorithm.


## 1. Introduction

VLSI technology has made possible the integration of circuits with hundreds of thousands of components into a single silicon chip. This high level of integration opens the way for massive parallel computations. Systolic processing constitutes a feasible solution for massive parallel computations. Its principles are compatible with VLSI technology characteristics [8]. Since systolic arrays are highly regular, only algorithms with repetitive computations perform well on them. Algorithms with nested loops fall into this category.

An important problem associated with designing systolic arrays is the mapping algorithm into systolic array architecture. Several techniques have been proposed for this purpose. Particularly useful here is the approach based on space-time representation of computation structure [1-10]. This method may be also used to examine the performances of possible systolic array implementation. Various criteria can be used to compare the performances of systolic arrays. The array size, which is defined as the number of processors in the array, obviously determines the basic hardware cost.

[^0]Therefore a systolic array (SA) which has a minimum number of processing elements (PE) gives the optimal solution with respect to this cost function.

The objective of this paper is to determine the minimal number of processing elements (PE) in the 2D systolic implementations for one class of nested loop algorithms, according to projection direction and size of loops. For given projection direction, $\mu$, we first introduce a linear transformation $H$, which maps index space $C_{D}$ into a new index space $\bar{C}_{D}$. This transformation accommodates $C_{D}$ to the projection direction $\mu$. When a space-time transformation, which maps index space into systolic array, is applied on $\bar{C}_{D}$ the result is a 2 D systolic array with minimal number of PEs.

The rest of the paper is organized as follows. Section 2 contains background and problem definition. In section 3 we define a class of adaptable algorithms. In section 4 we define a one-to-one mappings of index space for adaptable algorithms, and determine minimal number of PEs in the 2D systolic array implementation. Then we compare obtained results with those found in the literature.

## 2. Background

Each regular 3-nested loop algorithm can be characterized by a pair $\left(D, C_{D}\right)$ (see for example [7-9]), where $D$ is data dependency matrix and $C_{D}=\left\{(i, j, k) \mid 1 \leq i \leq N_{1}, 1 \leq j \leq N_{2}, 1 \leq k \leq N_{3}\right\}$ is the index space where the data are used or computed. The systolic array implementation can be obtained by a linear transformation

$$
T=\left[\begin{array}{c}
\Pi  \tag{2.1}\\
-- \\
S
\end{array}\right]=\left[\begin{array}{ccc}
t_{11} & t_{12} & t_{13} \\
-- & -- & -- \\
t_{21} & t_{22} & t_{23} \\
t_{31} & t_{32} & t_{33}
\end{array}\right],
$$

where $\Pi$ determines time scheduling, and $S$ is the space mapping function determining PE locations and the communication channels between them. If matrix $T$ is nonsingular, i.e. det $T \neq 0$, and all elements of $\Delta_{t}=\Pi D$ are positive (or negative depending on convention), it is said that $T$ is valid space-time transformation of $\left(D, C_{D}\right)$ denoted as

$$
\begin{equation*}
T\left(D, C_{D}\right)=\left(\Delta, C_{\Delta}\right) \tag{2.2}
\end{equation*}
$$

where

$$
\Delta=\left(\Delta_{t}, \Delta_{s}\right), \quad \Delta_{t}=\Pi D, \quad \Delta_{s}=S D, \quad C_{\Delta}=\left[\begin{array}{lll}
t & x & y
\end{array}\right]^{T}
$$

and

$$
t=\Pi\left[\begin{array}{lll}
i & j & k
\end{array}\right]^{T}, \quad\left[\begin{array}{ll}
x & y
\end{array}\right]^{T}=S\left[\begin{array}{lll}
i & j & k
\end{array}\right]^{T} \quad \text { for all }\left[\begin{array}{lll}
i & j & k
\end{array}\right]^{T} \in C_{D}
$$

Vector $[x y]^{T}$ determines the $x-y$ coordinates of the PE in the projection plane. Several designing tools have been proposed for finding valid transformations $T$ [1, 7-9].

Each transformation matrix $T$ defined by (2.1) is associated with unique direction projection $\mu=\left[\mu_{1} \mu_{2} \mu_{3}\right]^{T}$, for which the following is valid

$$
\begin{equation*}
S \cdot \mu=0 \tag{2.3}
\end{equation*}
$$

It is assumed that rows of matrix $S$ are linearly independent, i.e. that $\operatorname{rank} S=2$.

As we have already mentioned we are looking for transformations that give the smallest number of PEs in the 2D systolic arrays. For the sake of comparison, we will first present the corresponding results obtained in [11] (see also [12] for 3-nested loop algorithm. The expression for number of processing elements, $\Omega_{p}$, depends only on space-time transformation, $T$, and the size of loops $\left(N_{1}, N_{2}, N_{3}\right)$.

Theorem 1 ([11]). Let $\omega=\left(N_{1}-a_{1}\right)\left(N_{2}-a_{2}\right)\left(N_{3}-a_{3}\right)$. Then

$$
\Omega_{p}= \begin{cases}N_{1} N_{2} N_{3}, & \text { if } a_{i}>N_{i} \text { for some } 1 \leq i \leq 3  \tag{2.4}\\ N_{1} N_{2} N_{3}-\omega, & \text { otherwise }\end{cases}
$$

where

$$
a_{i}=\left|\frac{T_{1 i}}{\operatorname{gcd}\left(T_{11}, T_{12}, T_{13}\right)}\right|
$$

In the previous expression, $T_{1 i}, i=1,2,3$ is $(1, i)-$ cofactor of matrix $T$, while $\operatorname{gcd}\left(T_{11}, T_{12}, T_{13}\right)$ denotes the greatest common divisor of the nonzero integers, $T_{11}, T_{12}$ and $T_{13}$. It is obvious that the expression (2.4) for $\Omega_{p}$ depends only on transformation $T$ and the size of loops $N_{1}, N_{2}$ and $N_{3}$. But, if we take into account some properties of the algorithm, the result can be optimized. Namely, there is a broad class of algorithms with the property that index space $C_{D}$ can be accommodated to the projection direction $\mu$. This accommodation is performed by one-to-one mapping $H: \quad C_{D} \rightarrow \bar{C}_{D}$, where $H$ depends on $\mu$. If we then apply transformation $T$ on $\bar{C}_{D}$ we obtain the set $C_{\Delta}$ with fewer number of processing elements.

## 3. Definitions

In this section, we give some preliminary definitions as a basis for the description that follows.

Let $\mathcal{A}$ be a regular 3 -nested loop algorithm with index space $C_{D}=$ $\left\{(i, j, k) \mid 1 \leq i \leq N_{1}, 1 \leq j \leq N_{2}, 1 \leq k \leq N_{3}\right\}$. We introduce the following subclasses of $\mathcal{A}$.
Definition 1. If the ordering of computations in algorithm $\mathcal{A}$, for some fixed $j$ ( $i$ ), may be performed over arbitrary permutations of index variables $i$ and $k(j$ and $k)$, we say that $\mathcal{A}$ is $\mathcal{A}(i, k)(\mathcal{A}(j, k))$ adaptable.

Remark 1. If a given algorithm $\mathcal{A}$ is both $\mathcal{A}(i, k)$ and $\mathcal{A}(j, k)$ adaptable, we say that it is adaptable.

In the sequel we define one-to-one mappings for adaptable algorithms which in composition with $T$ enable to obtain 2D systolic arrays with minimal number of processing elements.

## 4. One-to-one Mappings for Adaptable Algorithms

Let $\mathcal{A}$ be an algorithm characterized by a pair $\left(D, C_{D}\right)$ and valid transformation $T$. Let $\mu=\left[\mu_{1} \mu_{2} \mu_{3}\right]^{T}$ be a projection which corresponds to $T$. The accommodation of index space $C_{D}$ to the direction $\mu$ is performed by " $1-1$ " mapping $H=(F, G), \quad H: \quad C_{D} \rightarrow \bar{C}_{D}$, where $F$ is $3 \times 3$ matrix whose elements depend on $\mu$, and $G$ is $3 \times 1$ matrix with constant coefficients. Matrix $G$ elements are determined from the condition that $H$ performs mapping from the first into the first octant of Euclidian space. The definition of $H$ for adaptable algorithms is as follows:

Definition 2. Suppose that a given algorithm is of type $\mathcal{A}(i, k)$. If $\mu=$ $\left[\mu_{1} \mu_{2} \mu_{3}\right]^{T}$ is allowable projection direction with $\mu_{2}=1$, then mapping $H=(F, G)$ is defined by

$$
F=\left[\begin{array}{ccc}
1 & \mu_{1} & 0  \tag{4.1}\\
0 & 1 & 0 \\
0 & \mu_{3} & 1
\end{array}\right], \quad G=\left[\begin{array}{c}
g_{1} \\
0 \\
g_{3}
\end{array}\right],
$$

where $g_{1}$ and $g_{3}$ are smallest integers determined such that for each $[i j k]^{T} \in$ $C_{D}$ the following is valid

$$
\begin{equation*}
u=i+\mu_{1} j+g_{1}>0, \quad w=k+\mu_{3} j+g_{3}>0 . \tag{4.2}
\end{equation*}
$$

The elements $u$ and $w$ are obtained according to

$$
\left[\begin{array}{l}
u  \tag{4.3}\\
v \\
w
\end{array}\right]=F\left[\begin{array}{l}
i \\
j \\
k
\end{array}\right]+G=\left[\begin{array}{ccc}
1 & \mu_{1} & 0 \\
0 & 1 & 0 \\
0 & \mu_{3} & 1
\end{array}\right] \cdot\left[\begin{array}{l}
i \\
j \\
k
\end{array}\right]+\left[\begin{array}{c}
g_{1} \\
0 \\
g_{3}
\end{array}\right]
$$

Remark 2. If $\mu_{2}=-1$, then $\mu_{1}$ and $\mu_{3}$ in (4.1), (4.2) and (4.3) should be substituted by $\left(-\mu_{1}\right)$ and $\left(-\mu_{3}\right)$, respectively.
Definition 3. Suppose that a given algorithm is of type $\mathcal{A}(j, k)$. If $\mu=$ $\left[\mu_{1} \mu_{2} \mu_{3}\right]^{T}$ is allowable projection direction with $\mu_{1}=1$, then mapping $H=(F, G)$ is defined by

$$
F=\left[\begin{array}{ccc}
1 & 0 & 0  \tag{4.4}\\
\mu_{2} & 1 & 0 \\
\mu_{3} & 0 & 1
\end{array}\right], \quad G=\left[\begin{array}{c}
0 \\
g_{2} \\
g_{3}
\end{array}\right],
$$

where $g_{2}$ and $g_{3}$ are smallest integers determined such that for each $[i j k]^{T}$ $\in C_{D}$ the following is valid

$$
\begin{equation*}
v=\mu_{2} i+j+g_{2}>0, \quad w=\mu_{3} i+k+g_{3}>0 \tag{4.5}
\end{equation*}
$$

The elements $v$ and $w$ are obtained according to

$$
\left[\begin{array}{l}
u  \tag{4.6}\\
v \\
w
\end{array}\right]=F\left[\begin{array}{l}
i \\
j \\
k
\end{array}\right]+G=\left[\begin{array}{lll}
1 & 0 & 0 \\
\mu_{2} & 1 & 0 \\
\mu_{3} & 0 & 1
\end{array}\right] \cdot\left[\begin{array}{l}
i \\
j \\
k
\end{array}\right]+\left[\begin{array}{c}
0 \\
g_{2} \\
g_{3}
\end{array}\right]
$$

Remark 3. If $\mu_{1}=-1$, then $\mu_{2}$ and $\mu_{3}$ in (4.4), (4.5) and (4.6) should be substituted by $\left(-\mu_{2}\right)$ and $\left(-\mu_{3}\right)$, respectively.

Before we determine the number of PEs in the systolic array, let us point out to some properties of mapping $H=(F, G)$ defined by (4.4) or (4.1):

- The mapping $H=(F, G)$ is " $1-1$ ";
- Suppose that $H=(F, G), \quad H: \quad C_{D} \rightarrow \bar{C}_{D}$ is mapping defined by (4.4) (or (4.1)). Then each line parallel with direction $\mu=\left[1 \mu_{2} \mu_{3}\right]^{T}$ (or $\mu=\left[\mu_{1} 1 \mu_{3}\right]^{T}$ ) which passes through one point of $\bar{C}_{D}$ contains $N_{1}$ (i.e., $N_{2}$ ) points from $\bar{C}_{D}$. There are $N_{2} N_{3}$ (i.e. $N_{1} N_{3}$ ) such lines.
- The composition of $T$ and $F$, i.e., $M=T \circ F$, is a regular mapping.

In the remainder of this section we will determine the minimal number of PEs in 2D systolic implementation for adaptable algorithms.

Theorem 2. Suppose that a given algorithm $\mathcal{A}$ is $\mathcal{A}(i, k)$ adaptable. The number of PEs in the 2D array obtained by the projection direction $\mu=$ $\left[\begin{array}{lll}\mu_{1} & 1 & \mu_{3}\end{array}\right]^{T}$ is

$$
\begin{equation*}
\Omega_{p}=N_{1} N_{3} . \tag{4.7}
\end{equation*}
$$

Proof. Suppose that algorithm $\mathcal{A}$ is characterized by a pair ( $D, C_{D}$ ), $C_{D}=\left\{(i, j, k) \mid 1 \leq i \leq N_{1}, 1 \leq j \leq N_{2}, 1 \leq k \leq N_{3}\right\}$, and valid transformation $T$, defined by (2.1). Since the algorithm is of $\mathcal{A}(i, k)$ type we can apply mapping $H=(F, G)$ defined by (4.1). The systolic array implementation is obtained according to composite mapping $T \circ H$, i.e., according to

$$
\left(C_{D}\right) \stackrel{H}{\longleftrightarrow}\left(\bar{C}_{D}\right) \quad \text { and } \quad\left(D, \bar{C}_{D}\right) \stackrel{T}{\longrightarrow}\left(\Delta, C_{\Delta}\right) .
$$

Since $G$ is matrix with constant coefficients, the number of PEs, $\Omega_{p}$, in the array depends only on matrix $M=T \circ F$, that is

$$
\begin{align*}
M=T \circ F & =\left[\begin{array}{lll}
t_{11} & t_{12} & t_{13} \\
t_{21} & t_{22} & t_{23} \\
t_{31} & t_{32} & t_{33}
\end{array}\right] \cdot\left[\begin{array}{ccc}
1 & \mu_{1} & 0 \\
0 & 1 & 0 \\
0 & \mu_{3} & 1
\end{array}\right]  \tag{4.8}\\
& =\left[\begin{array}{lll}
t_{11} & \mu_{1} t_{11}+\mu_{2} t_{12}+\mu_{3} t_{13} & t_{13} \\
t_{21} & 0 & t_{23} \\
t_{31} & 0 & t_{33}
\end{array}\right] .
\end{align*}
$$

Note that in (4.8) we have used the condition (2.3), $S \cdot \mu=0$, i.e., $\mu_{1} t_{21}+\mu_{2} t_{22}+\mu_{3} t_{23}=0$ and $\mu_{1} t_{31}+\mu_{2} t_{32}+\mu_{3} t_{33}=0$. Since $M$ is valid transformation and $M_{11}=M_{13}=0$, then according to Theorem 1 we have that $a_{1}=0, \quad a_{2}=1, \quad a_{3}=0$, i.e.,

$$
\Omega_{p}=N_{1} N_{2} N_{3}-N_{1}\left(N_{2}-1\right) N_{3}=N_{1} N_{3}
$$

Theorem 3. Suppose that a given algorithm $\mathcal{A}$ is $\mathcal{A}(j, k)$ adaptable. The number of PEs in the 2D array obtained by the projection direction $\mu=$ $\left[\begin{array}{lll}1 & \mu_{2} & \mu_{3}\end{array}\right]^{T}$ is

$$
\begin{equation*}
\Omega_{p}=N_{2} N_{3} . \tag{4.9}
\end{equation*}
$$

The proof is similar to that of Theorem 2.

Corollary 1. Suppose that a given algorithm $\mathcal{A}$ is adaptable. The number of PEs in the 2D array obtained by the projection directions $\mu=\left[\begin{array}{lll}1 & 1 & \mu_{3}\end{array}\right]^{T}$, or $\mu=\left[\begin{array}{lll}1 & -1 & \mu_{3}\end{array}\right]^{T}$, is

$$
\begin{equation*}
\Omega_{p}=N_{3} \cdot \min \left\{N_{1}, N_{2}\right\} \tag{4.10}
\end{equation*}
$$

Remark 4. We assume that directions $\mu$ and $-\mu$ are equal.
Remark 5. If for a given algorithm $\mathcal{A}$ allowable direction is $\mu=\left[\begin{array}{lll}0 & 0 & 1\end{array}\right]^{T}$, we have a trivial case $F=I$ and $G=0$. In that case

$$
\begin{equation*}
\Omega_{p}=N_{1} N_{2} \tag{4.11}
\end{equation*}
$$

Let us point out that for adaptable algorithms results obtained according to (2.4) are inferior compared to those obtained according to (4.7), (4.9) or (4.10). We will illustrate this fact on the example of matrix multiplication algorithm.

$$
\begin{aligned}
& \text { Algorithm (matrix multiplication } C=A \times B) \\
& \text { for } k:=1 \text { to } N_{3} \text { do } \\
& \text { for } j:=1 \text { to } N_{2} \text { do } \\
& \text { for } i:=1 \text { to } N_{1} \text { do } \\
& a(i, j, k):=a(i, j-1, k) \\
& \quad b(i, j, k):=b(i-1, j, k) ; \\
& c(i, j, k):=c(i, j, k-1)+a(i, j, k) * b(i, j, k) \text {; }
\end{aligned}
$$

where $a(i, 0, k) \equiv a_{i k}, b(0, j, k) \equiv b_{k j}, c(i, j, 0) \equiv 0$ for all $i, j$ and $k$. It is not difficult to conclude that a given algorithm is both of type $\mathcal{A}(i, k)$ and $\mathcal{A}(j, k)$. For the purpose of comparison we will take the same valid transformations $T_{1}$ and $T_{2}$ as in [11], that is

$$
T_{1}=\left[\begin{array}{ccc}
1 & 1 & 1 \\
-1 & 1 & 0 \\
0 & 0 & -1
\end{array}\right] \quad \text { and } \quad T_{2}=\left[\begin{array}{ccc}
1 & 1 & 1 \\
0 & 1 & 1 \\
1 & 0 & 1
\end{array}\right]
$$

The projection direction which corresponds to $T_{1}$ is $\mu=\left[\begin{array}{lll}1 & 1 & 0\end{array}\right]^{T}$. Accordingly, we can use Corollary 1 to determine the number of PEs in the corresponding systolic array. According to (4.10) we have

$$
\begin{equation*}
\Omega_{p}\left(T_{1}\right)=N_{3} \cdot \min \left\{N_{1}, N_{2}\right\} \tag{4.12}
\end{equation*}
$$

compared to

$$
\Omega_{p}\left(T_{1}\right)=N_{3} \cdot\left(N_{1}+N_{2}-1\right)
$$

obtained according to Theorem 1 (see [11]).
Similarly, for $T_{2}$ the corresponding direction is $\mu=\left[\begin{array}{lll}1 & 1 & -1\end{array}\right]^{T}$. Thus, according to Corollary 1

$$
\Omega_{p}\left(T_{2}\right)=\Omega_{p}\left(T_{1}\right)=N_{3} \cdot \min \left\{N_{1}, N_{2}\right\}
$$

compared to

$$
\Omega_{p}\left(T_{2}\right)=N_{1} N_{2} N_{3}-\left(N_{1}-1\right)\left(N_{2}-1\right)\left(N_{3}-1\right)
$$

obtained by the Theorem 1 (se [11]).
Similar results are obtained for all other allowable projection directions $\left(\mu=\left[\begin{array}{lll}1 & 0 & 0\end{array}\right]^{T}, \mu=\left[\begin{array}{lll}0 & 1 & 0\end{array}\right]^{T}, \mu=\left[\begin{array}{lll}0 & 0 & 1\end{array}\right]^{T}, \mu=\left[\begin{array}{lll}1 & 0 & 1\end{array}\right]^{T}, \mu=\left[\begin{array}{lll}0 & 1 & 1\end{array}\right]^{T}\right.$, $\mu=\left[\begin{array}{lll}1 & 1 & 1\end{array}\right]^{T}, \mu=\left[\begin{array}{lll}1 & -1 & 1\end{array}\right]^{T}, \mu=\left[\begin{array}{lll}1 & -1 & -1\end{array}\right]^{T}$ ) for a matrix multiplication algorithm.

Figures 1 and 2 show systolic array implementations obtained by $T_{2}$ for the case $N_{1}=N_{2}=N_{3}=2$ obtained according to Theorem 1 and Corollary 1 , respectively.


Fig. 1. Systolic array obtained according to Theorem 1

## 5. Conclusion

In this paper we have determined the minimal number of PEs in the 2D systolic implementations for one class of 3-nested loop algorithms. We


Fig. 2. Systolic array obtained according to Corollary 1
have defined a class of adaptable algorithms for which we introduce some linear transformations that accommodate the index space of algorithm to the projection direction. This accommodation enables us to obtain 2D SAs with the smallest number of PEs. The number of PEs depends on the size of loops and projection direction. We have illustrated the obtained results on the matrix multiplication algorithm.

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