# An Efficient Method for Generic DSP 

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## Introduction

Dilated convolution has an inherent property of capturing wider context in an image and longterm temporal characteristics in an audio signal. We propose a new scheme that allows efficient/generic implementation of 2D Dilated convolution and stride on typical DSPs where the instruction sets are well tuned for standard 1D and 2D filtering and convolution operations.
In this proposal an existing flexible and efficient standard 2D convolution implementation with stride support forms the basic building block to implement Dilated convolution with stride. Thereby, 2D-dilated convolution is equivalently represented as several smaller convolutions with appropriate matrix slicing and re-ordering.

## Dilation \& Stride

2D Dilation in literature referred to as atrous convolution or convolution with holes. Dilation introduces 'zeros' in the kernel matrix of the convolution. An example of pre/post kernel dilation with a factor 2 in height $d_{h}$ and width $d_{w}$ shown below,

$$
\xrightarrow{K_{w}}
$$

Matrices post dilated convolution are generally strided to reduce the dimensions of the output. Stride simply-put is skipping the matrix values by a factor. Stride and Dilation in mathematical form for 2 D matrix is as below:
$Y\left(x_{3}, y_{3}\right)$
$=\sum_{0 \leq x_{2}<K_{h}} \sum_{0 \leq y_{2}<K_{w}} I\left(\begin{array}{c}x_{2} * d_{h}+x_{3} * s_{h}, \\ y_{2} * d_{w}+y_{3} * s_{w} \\ F\left(x_{2}, y_{2}\right)\end{array}\right) *$
Where, $I$ the input matrix, $F$ kernel matrix and $s_{w} / s_{h}$ are the stride factors in width and height dimension, $0 \leq y_{3}<\left\lfloor\left(I_{w}-K_{w_{-} D}\right) / s_{w}\right\rfloor+1$ and $0 \leq x_{3}<\left\lfloor\left(I_{h}-K_{h_{-} D}\right) / s_{h}\right\rfloor+1$

The input matrices are assumed to be appropriately zero padded, if needed, such that input width and input height are always gr. than equal to kernel dimension i.e., $I_{w} \geq K_{w_{-} D}$ and $I_{h} \geq K_{h_{-} D}$.

## A Novel scheme for Dilation and Stride

Dilated convolution in comparison to non-dilation increases the computational complexity by the order of the product of dilation factors in height and width dimension using atrous method. We propose a joint solution for dilation and stride. As a special case, the complexity is immune to the dilation factor when stride is unity.

## Dilation Scheme

Implementation of Dilated convolution split into three steps: a) Input Slicing b) Standard convolution c) Output stitching. An existing standard convolution forms the central computation block and input-Slicing/output-stitching are the memory alignment processes. Below an illustration of a 7X5 matrix for dilation factor of 2 in height and width.


| Convolution |  |
| :---: | :---: |
| sub-matrices with kerne convolution output sub-m $Y_{n_{1} n_{2} d_{h}, d_{w}}\left(x_{n}^{\sim}\right.$ $=\sum_{0 \leq x_{2}<K_{n}} \sum_{0 \leq y_{2}<K_{w}}$ | convolved using std generating rices $\tilde{n}_{n}^{\sim}$ $n_{2} d_{h} d_{w}\binom{x_{2}+x_{n}^{\sim}}{y_{2}+y_{n}^{\tilde{n}}}$ $\left(x_{2}, y_{2}\right)$ |
| sub-matrix ${ }_{00}$ (Red,Cyan) | sub-matrix ${ }_{01}$ (Red,Black) |
| sub-matrix ${ }_{10}$ (Yellow,Cyan) | sub-matrix ${ }_{11}$ (Yellow,Black) |

## Stitching

sub-matrix convolved with kernel using std convolution generating output submatrices
$Y\left(n_{1}+x_{n}^{\sim} * d_{h}, n_{2}+y_{n}^{\sim} * d_{w}\right)$
$=Y_{n_{1} n_{2} d_{h}, d_{w}}\left(x_{n}^{\sim}, y_{n}^{\sim}\right)$


## Stride Scheme

The skipped values of convolved output by a pre-defined factor is given by stride. The scheme for stride is proposed in the dilation framework as explained above i.e., slicing/convolution/stitching

## Problem Statement

From the 'stitching' step the output values of interest after applying stride can be written as,

$$
\begin{aligned}
& Y\left(s_{h} * x, s_{w} * y\right) \\
& =Y\left(n_{1}+x_{n}^{\sim} * d_{h}, n_{2}+y_{n}^{\sim} * d_{w}\right)
\end{aligned}
$$

Where, $s_{h}$ and $s_{w}$ are stride in height and width dimension. In other words, matrix values with integer coordinates of $\langle x, y\rangle$ are values of interest as shown below.

$$
\begin{aligned}
& <x, y>= \\
& <\frac{n_{1}+x_{n}^{\sim} * d_{h}}{s_{h}}, \frac{n_{2}+y_{n}^{\sim} * d_{w}}{s_{w}}>
\end{aligned}
$$

## Alternate Statement

S1: For a given offset pair $\left\langle n_{1}, n_{2}\right\rangle$ find the minimum value of coordinates $<x_{n}^{\sim}, y_{n}^{\sim}>$ say, < $x_{n_{-} \min }^{\sim}, y_{n_{-} \min }^{\sim}>$
S2: From the initial values $<x_{n_{-} \text {min }}^{\sim}$ $y_{n_{\_} \text {min }}^{\sim}>$ for a given $<n_{1}, n_{2}>$ find successive values of $\left\langle x_{n}^{\sim}, y_{n}^{\sim}>\right.$

## Solution

Postulate: Assume S1 is true i.e., for a given $<\mathrm{n}_{1}, \mathrm{n}_{2}>$ there exist a $<$ $\mathrm{x}_{\mathrm{n}_{-} \min }, \mathrm{y}_{\mathrm{n}_{-} \min }>$. Finding solution for S 2 i.e., to find the successive values of $\left\langle\mathrm{x}_{\mathrm{n}}^{\sim}, \mathrm{y}_{\mathrm{n}}^{\sim}\right\rangle$ after the initial value $\left.<\mathrm{x}_{\mathrm{n}_{\mathrm{\prime}} \min }^{\sim}, \mathrm{y}_{\mathrm{n}_{\sim} \min }^{\sim}\right\rangle$
Inference: Let the next successive value of $\left\langle x_{n}^{\sim}, y_{n}^{\sim}\right\rangle$ after $<x_{n_{-}}^{\sim}$ min , $y_{n_{-} \text {min }}^{\sim}>$ be $<\underset{n_{-} \text {min }}{\sim}+\Delta_{x}, y_{n_{-} \text {min }}^{\sim}+\Delta_{y}>$. Inserting these values.

$$
\begin{gathered}
<x, y>=<\frac{n_{1}+\left(x_{n \_\min }^{\sim} * d_{h}\right)}{s_{h}}+\frac{\Delta_{x} * d_{h}}{s_{h}} \\
\frac{n_{2}+\left(y_{n \_ \text {min }}^{\sim} * d_{w}\right)}{s_{w}}+\frac{\Delta_{y} * d_{w}}{s_{w}}>
\end{gathered}
$$

The minimum value of $\Delta_{x} \& \Delta_{y}$ to contribute an integer value $\langle x, y\rangle$ is

$$
\Delta_{x}, \Delta_{y}=\frac{s_{h}}{G C D\left(s_{h}, d_{h}\right)}, \frac{s_{w}}{G C D\left(s_{w}, d_{w}\right)}
$$

Therefore $<\Delta_{x}, \Delta_{y}>$ is the periodic pattern for chosen value of dilation and stride. Extending this periodic property, it is sufficient to check the first $<\Delta_{x}, \Delta_{y}>$ elements to test the validity of statement S 1 .

## Highlights:

- A sub-matrix $\left\langle\mathrm{n}_{1}, \mathrm{n}_{2}\right\rangle$ not satisfying $\mathrm{S} 1 \Rightarrow$ no participation in convolution
- $\Delta_{x} \& \Delta_{y}$ are the modified stride values for sub-matrix convolution
- Upon re-ordering $\frac{d_{h}}{G C D\left(s_{h}, d_{h}\right)}, \frac{d_{w}}{\operatorname{GCD}\left(s_{w}, d_{w}\right)}$ is the output stride

$$
\begin{gathered}
\text { Re-ordering stride output } \\
Y\left(\frac{h_{\text {offset }}\left(n_{1}\right)+i_{1} * R_{h}}{s_{h}}, \quad \frac{w_{\text {offset }}\left(n_{2}\right)+i_{2} * R_{w}}{s_{w}}\right) \\
\left.=Y_{n_{1} n_{2} d_{h}, d_{w} s_{h} s_{w}\left(i_{1}, i_{2}\right)}\right) \\
n_{1}=0,1,2, \ldots, d_{h}-1 \\
n_{2}=0,1,2, \ldots, d_{w}-1 \\
h_{\text {offset }}\left(n_{1}\right)=n_{1}+x_{n_{n} \min }\left(n_{1}\right) * d_{h} \\
w_{\text {offset }}\left(n_{2}\right)=n_{2}+y_{n \_\min }^{\sim}\left(n_{2}\right) * d_{w} \\
R_{h}=\frac{s_{h}}{\operatorname{GCD}\left(d_{h}, s_{h}\right)} * d_{h} ; R_{w}=\frac{s_{w}}{\operatorname{GCD}\left(d_{w}, s_{w}\right)} * d_{w}
\end{gathered}
$$

Result
The proposed method of decomposition is compared against atrous method. The method implemented on Cadence's Tensilica HiFi5 processor with NN extension simulator assuming zero memory wait states. Input/kernel data format ( $\mathrm{N}, \mathrm{H}, \mathrm{W}, \mathrm{C}$ ). An improvement of 30 X (cycles) can be observed for dilation factor of 16. Scratch memory reduction for the proposed method observed. The implementation is available on Cadence's NN HiFi5 GitHub link.

| Dilation <br> Factor | Decomposition <br> Method |  | Zero Insertion (ZI) <br> Method |  |
| :---: | :---: | :---: | :---: | :---: |
| (Stride=2) | Cycles <br> $\left(\mathrm{X} 10^{6}\right)$ | Scratch <br> Memory <br> $(\mathrm{KB})$ | Cycles <br> $\left(\mathrm{X} 10^{6}\right)$ | Scratch <br> Memory <br> $(\mathrm{KB})$ |
|  |  |  |  |  |
| 2 | 1.94 | 6.14 | 4.89 | 20.20 |
| 4 | 2.01 | 3.14 | 10.01 | 36.33 |
| 8 | 2.14 | 1.64 | 26.54 | 68.58 |
| 16 | 2.32 | 0.89 | 69.70 | 133.08 |

Computational gain for different Dilation and Stride values published in paper

