# Compiler-Directed Memory Hierarchy Design for Low-Energy Embedded Systems



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## Outline

- Memory management for embedded signal processing applications
- **The problem:** Memory hierarchy design for low-energy
- The model: Polyhedral framework for memory management
- The algorithms: Energy-aware assignment to memory layers

  Energy-aware memory banking
- Experimental results and conclusions



## Low-Power Memory Management

Real-time multidimensional signal processing systems (video and image processing, telecommunications, audio and speech coding, medical imaging, etc.)

The **performance+energy+area** of the whole system are significantly influenced by *the memory subsystem* 

Gap between processor and memory speed memory unable to provide data and instructions at the pace required by the processor

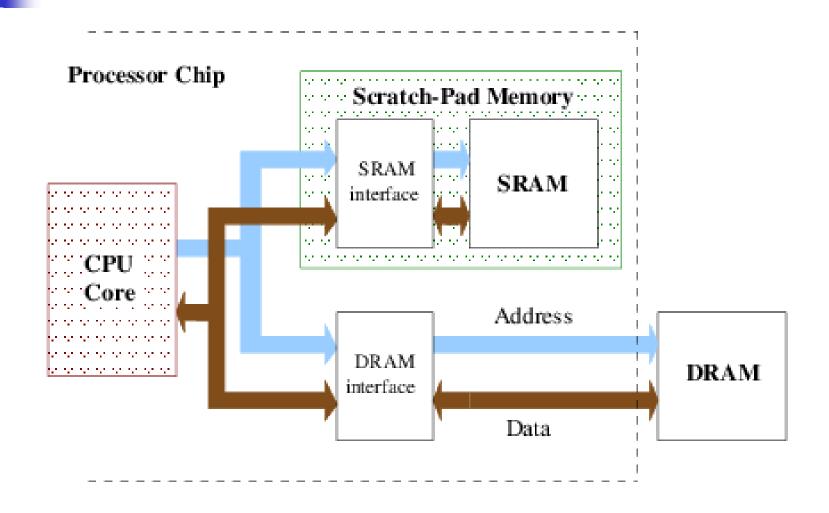
"Memory Wall" [Wulf & McKee 1995] or "Memory Bottleneck"



## Advanced memory architectures based on the concept of memory hierarchy

- lower levels in the hierarchy are made of small memories, close and tightly coupled to the computation units
- higher levels are made of increasingly large memories, far from the computation units
- the terms close and far refer to the effort needed to fetch/store a given amount of data from/to the memory
- the effort can be expressed in units of time or energy depending on the cost function of interest

#### Simple Hierarchical Data Storage Organization





#### Low-Power Memory Management

SPMs vs. Caches
[Banakar, Marwedel & al. 2002]

in embedded systems

- **4** 34% smaller area than caches of same capacity
- **40% lower power consumption** than caches of same capacity
- 4 18% less clock cycles for a knapsack allocation algorithm (the access time of an SPM is typically within 1 clock cycle)



Scratchpad memories (SPMs) are on-chip SRAMs

The mapping of data to the SPM can be done statically

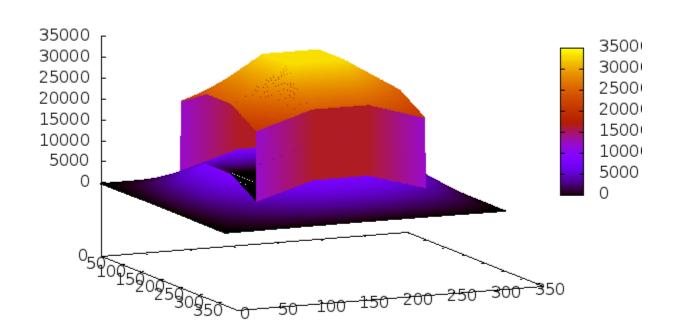


No need to check at run time the availability of data in the SPM

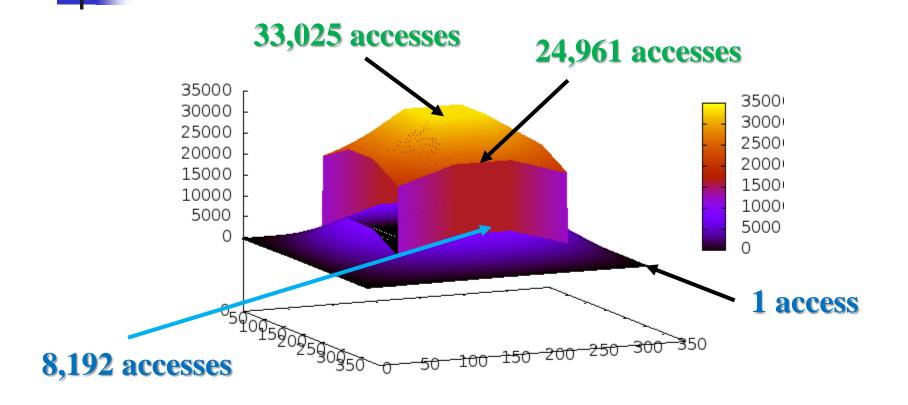
No need of comparators, of the miss/hit acknowledging logic

## Example of Behavioral Specification

```
C[0] = 0;
                                // input: int A[256][256]
for (int i=64; i<192; ++i) {
  for (int j=64; j<192; ++j) {
     B[i][j][0] = 0;
     for (int k=i-64; k < =i+64; ++k) {
        for (int l=j-64; k < = j+64; ++1) {
          B[i][j][129*k - 129*i + l - j + 8321] = A[i][j]
                -A[k][l] + B[i][j][129*k - 129*i + l - j + 8320];
     C[128*i + j - 8255] = B[i][j][16641] + C[128*i + j - 8256];
out = C[16384];
                                // output: out
```



Map of memory accesses to signal's A index space



Map of memory accesses to signal's A index space

#### The problem

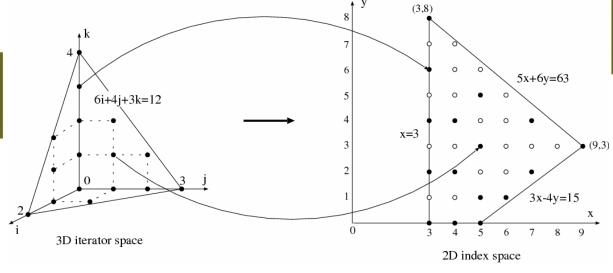
- the dynamic energy consumption per memory access is much smaller for the SPM than for external DRAM
- the arrays may have very non-uniform access patterns
   (the elements A[i][j] have 1 − 33,025 accesses)
- an array may need a lot of storage: it may not be possible to store it *all* within the SPM (array A needs 64 Kbytes)



Which array elements should be stored on-chip such that the (static+dynamic) energy consumption in the multi-layer memory subsystem be minimized?



3D iterator space



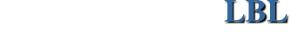
2D index space

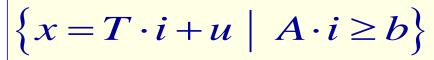
$$\begin{bmatrix} \mathbf{x} \\ \mathbf{y} \end{bmatrix} = \begin{bmatrix} \mathbf{1} & \mathbf{2} & \mathbf{0} \\ \mathbf{0} & \mathbf{1} & \mathbf{2} \end{bmatrix} \begin{bmatrix} \mathbf{i} \\ \mathbf{j} \\ \mathbf{k} \end{bmatrix} + \begin{bmatrix} \mathbf{3} \\ \mathbf{0} \end{bmatrix}$$





The array references represented as (linearly-bounded) lattices





Intuitive observation

The most intensely-accessed parts of an array are typically covered by several array references





Intersect the array references!



#### **Intersect lattices!**

LBL₁ ∩ LBL₂



$$\begin{cases} LBL_1 = \{ x = T_1 \cdot i_1 + u_1 \mid A_1 \cdot i_1 >= b_1 \} \\ \\ LBL_2 = \{ x = T_2 \cdot i_2 + u_2 \mid A_2 \cdot i_2 >= b_2 \} \end{cases}$$

$$LBL_2 = \{ x = T_2 \cdot i_2 + u_2 \mid A_2 \cdot i_2 >= b_2 \}$$



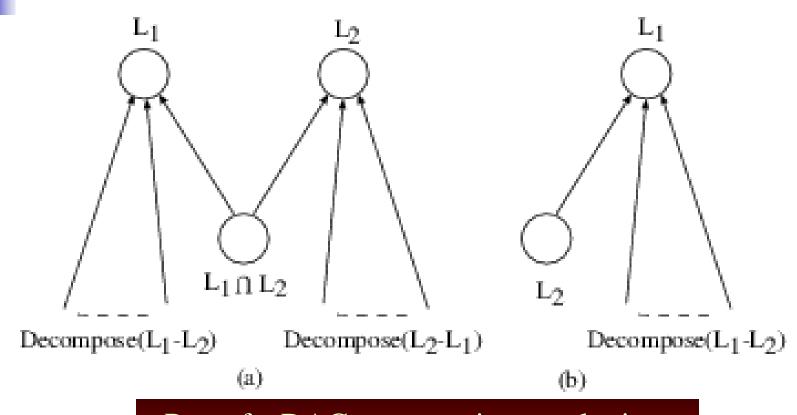


$$\mathbf{T}_1 \cdot \mathbf{i}_1 + \mathbf{u}_1 = \mathbf{T}_2 \cdot \mathbf{i}_2 + \mathbf{u}_2$$

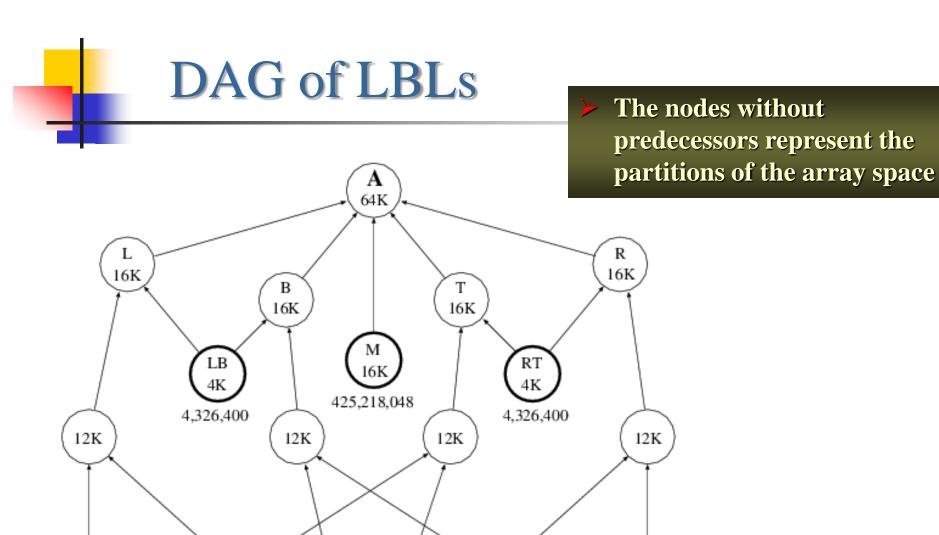
$$T_1 \cdot i_1 + u_1 = T_2 \cdot i_2 + u_2$$
 {  $A_1 \cdot i_1 >= b_1$ ,  $A_2 \cdot i_2 >= b_2$  }

Diophantine system of eqs.

New polytope



Part of a DAG representing two lattices whose intersection is not empty (the difference may comprise several lattices)



LT

4,326,400

25,692,160

MB

25,692,160

MT

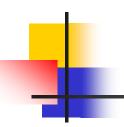
25,692,160

RB

4,326,400

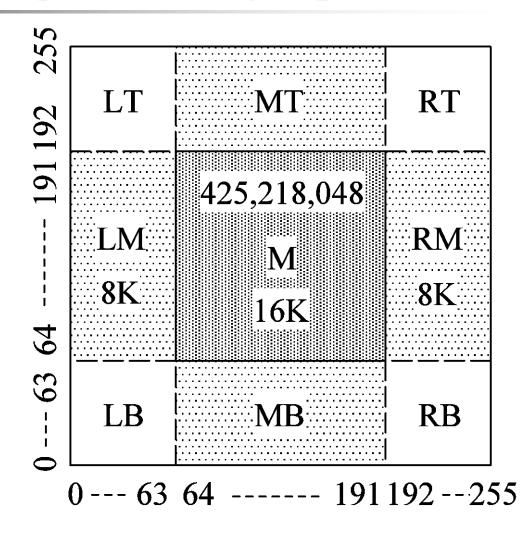
RM

25,692,160



## Partitioning the Array Space

The central part M
of the array space
of signal A
receives 78% of
the memory
accesses





#### The Assignment Algorithm

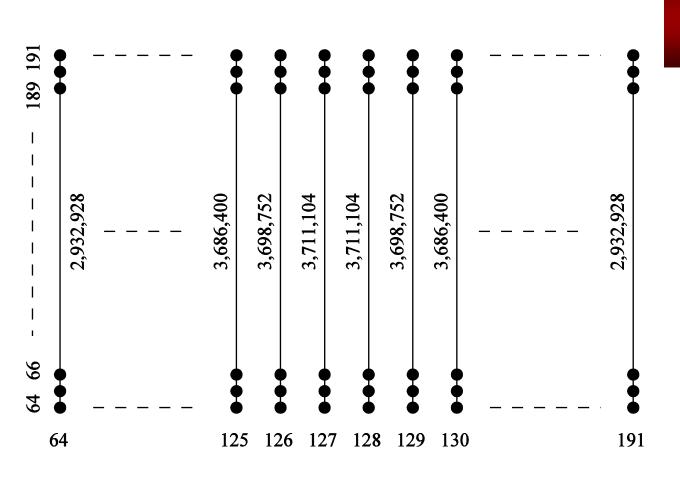
- focus on the LBLs whose assignment to the SPM layer would yield the largest energy reduction
- an LBL may need a lot of storage: it may not be possible to store it *all* within the SPM (lattice M needs 16 Kbytes)



What is to be done if the size of the SPM is too small relative to the storage requirement of a lattice?



#### Slicing the Large Lattices



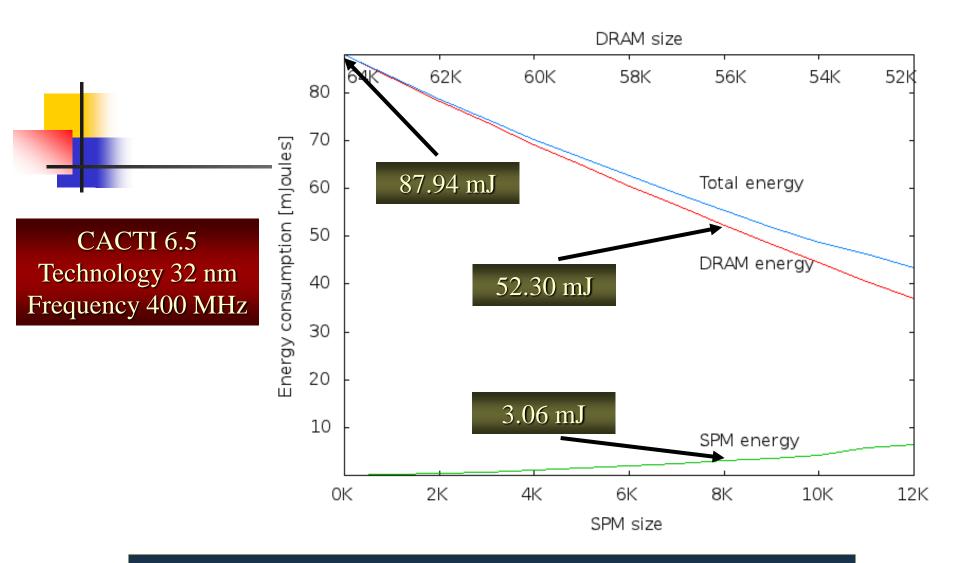
The lattice M of 16Kbytes is split

Fine-grain lattices of 128 bytes

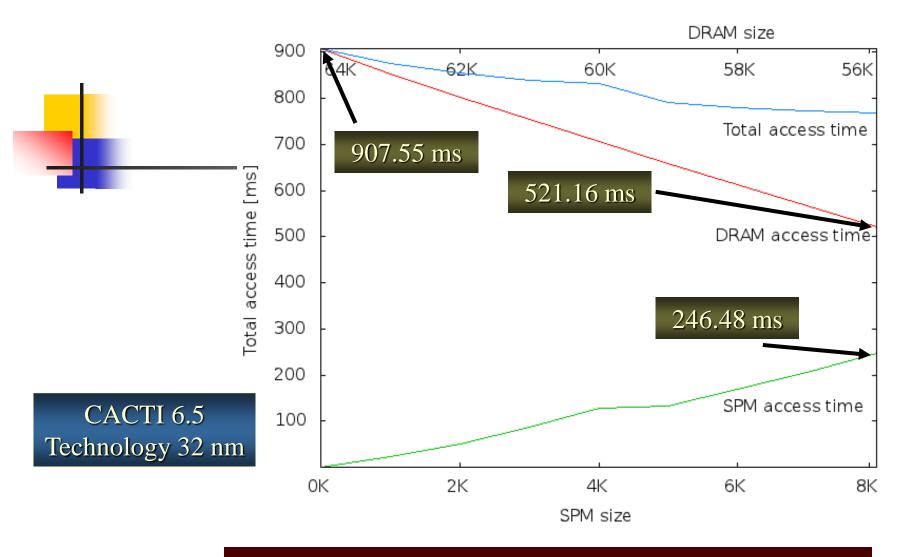


#### The Assignment Algorithm

```
for (each signal in the application code)
   partition its array space into disjoint LBLs;
initially, assign all the disjoint lattices L to the DRAM;
   size(DRAM) = \Sigma size(L); size(SPM) = 0;
for (each disjoint lattice L) compute the energy reduction if L is assigned to SPM;
do { select the lattice L yielding the largest reduction of energy;
     if (size(SPM) + size(L) <= MAX_SPM_SIZE)
        assign L to the SPM: size(SPM) += size(L); size(DRAM) -= size(L);
        update the energy benefits of all the lattices still assigned to the DRAM;
     else
        "slice" the lattice L relative to its next iterator and replace L by these LBLs;
        compute the energy benefits of these new 'finer-granularity' lattices;
  until (MAX SPM SIZE is reached | the max level of "slicing" is reached);
```



The graphs of energy consumption by the SPM, DRAM, and the 2-layer memory system storing the array A of 64 Kbytes



The graphs of total access time to the SPM, to the DRAM, and to the 2-layer memory system storing the array A of 64 Kbytes



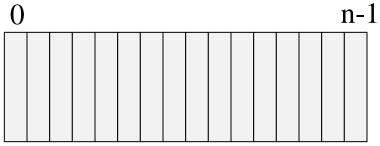
#### Motivation



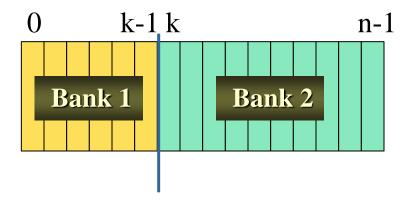
- ◆ Reduction of static & dynamic energy consumption with the size of the memory banks
- Possibility of turning on/off the banks independently

- Hardware cost overhead
- Energy overhead(but also time and area overhead)





Monolithic SPM



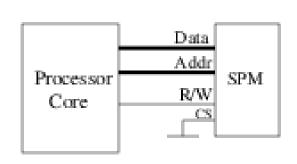
Beneficial partitioning

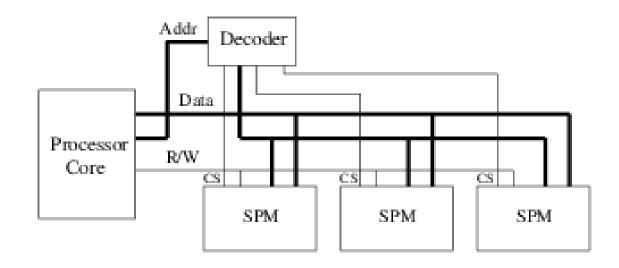


$$E_{Bank1} + E_{Bank2} + \Delta E_{12} < E_{Monolithic\_SPM}$$



#### On-chip Memory Banking





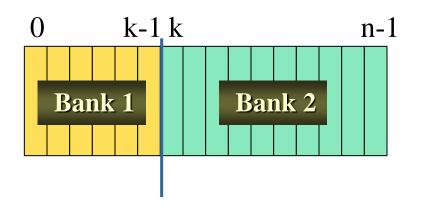
Architecture with monolithic SPM



Architecture with SPM partitioned in 3 banks

 $\Delta E_{13}$ 

Exhaustive exploration with backtracking Benini *et al.*, *IEEE Trans. CAD 2002* 



Optimal 2-way partitioning



 $Min_k\{E_{Bank1} + E_{Bank2}\} + \Delta E_{12}$ 

Using recursion



Optimal M-way partitioning

## Exhaustive exploration with backtracking Benini *et al.*, *IEEE Trans. CAD 2002*

- + for M = 2, 3 : optimal solutions
- + for M = 4 : optimal solution
- $\downarrow$  for M > 4





CPU: usually over 1 hour

Partitions: many billions

Exploration using dynamic programming Angiolini *et al.*, *IEEE Trans. CAD 2005* 

- Advantage: no need of presetting M
- ♣ Disadvantage: a huge data structure (matrix: | SPM | x | TraceAccesses | )



#### The Banking Algorithm

- Input 1
- maximum number of banks M

- Input 2
- ♣ array  $[\Delta E_{12}, \Delta E_{23}, ..., \Delta E_{M-1,M}]$ whose elements  $\Delta E_{k,k+1}$  are energy overheads implied by moving from k to k+1 banks
- **♦** Input 3
- array of SPM addresses where the lattices of signals are mapped into the on-chip memory
- Input 4
- array of R/W accesses for the on-chip lattices
- Output
- array of energetically-optimal bank boundaries

#### The Banking Algorithm

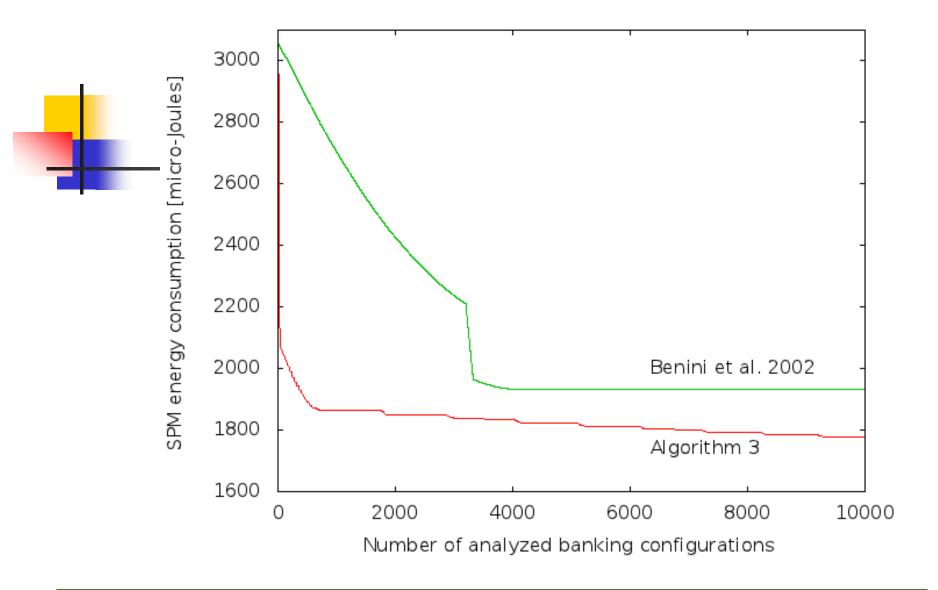
```
crtMinEnergy = SPM_energy (addr_0, addr_n);
                                                  Start from monolithic SPM
crtBestPartitioning = {addr_0, addr_n};
push (SolutionStack, crtBestPartitioning);
for (int i=1; i< n; i++)
                                                           First bank:
   EnergyConsumed = SPM_energy (addr_0, addr_i);
                                                          [addr<sub>0</sub>, addr<sub>i</sub>]
   if ( EnergyConsumed >= crtMinEnergy ) break;
   EnergyAvailable = crtMinEnergy - EnergyConsumed;
    Partitioning (2, M, i, EnergyConsumed, EnergyAvailable);
         Partition the address space [addr<sub>i</sub>, addr<sub>n</sub>] in at most M-1 banks
pop (SolutionStack);
print crtBestPartitioning, crtMinEnergy;
```

```
void Partitioning (m, M, i, EnergyConsumed, EnergyAvailable)
  if (EnergyAvailable \leq \Delta E_{m-1,m}) return;
   EnergyConsumed += \Delta E_{m-1.m};
   w = EnergyConsumed + SPM_energy (addr_i, addr_n);
   if ( w < crtMinEnergy )
   { crtMinEnergy = w ;
     crtBestPartitioning = top(SolutionStack) U {addr;};
   if ( m < M ) // if the maximum number of banks not reached yet
                // then explore finer partitions
   { push(SolutionStack, top(SolutionStack) U {addr; }) ;
     for (int k = i+1; k < n; k++)
         w = EnergyConsumed + SPM_energy ( addr<sub>i</sub> , addr<sub>k</sub> ) ;
         if ( w >= crtMinEnergy ) break; // no chance of a better
           // finer partition: the current min energy was reached
         Partitioning (m+1, M, k, w, crtMinEnergy - w);
     pop(SolutionStack);
```

Last bank: [addr<sub>i</sub>, addr<sub>n</sub>]
A better solution found !!

Bank m: [addr<sub>i</sub>, addr<sub>k</sub>]

Partition the address space  $[addr_k, addr_n]$  in at most M-m banks



Energy-aware SPM banking: the decrease of the SPM energy consumption as different SPM partitions are analyzed

Application	Scalars	Memory accesses	Energy DRAM [μJ]	SPM size	Energy savings DRAM+SPM	Energy savings [Brockmeyer]	CPU [sec]
Dynamic programming	21,082,751	83,834,000	2,515,020	32K	56.1 %	35.1 %	36.2
Motion estimation	265,633	864,900	25,947	1K	50.7 %	28.6 %	12.5
Durbin's algorithm	252,499	1,004,993	30,150	512	62.2 %	37.4 %	8.9
SVD updating	3,045,447	29,500,000	885,000	16K	46.5 %	28.2 %	24.5

Experimental Results on Signal Assignment to the On-Chip and Off-Chip Memory Layers (dynamic + static energy evaluations: CACTI 6.5)

#### **Experimental Results**

Application	Address space	CPU Full_Expl. (M=4) [sec]	CPU [sec] M=8	Energy savings vs. Full_Expl. (M=4)	Energy savings vs. monolithic SPM (M=8)
Motion detection	9,600	5,289	32.2	9.69 %	55.78 %
Motion estimation	1,024	736	5.3	7.51 %	47.21 %
Durbin's algorithm	512	247	2.3	7.28%	46.52 %
SVD updating	16,384	7,524	65.2	10.94 %	59.88 %

Experimental Results on Energy-Aware SPM Banking



#### **Conclusions**

- Integrated CAD methodology for system-level exploration, focusing on memory management tasks
- Energy-aware data assignment technique based on a library of operations with integral polyhedra and lattices
- ♣ The assignment algorithm could be extended for an arbitrary number of layers of memory hierarchy if the functions of energy spent per access and static power versus memory size were available for each layer
- Lenergy-aware banking algorithm based on the computation of the intensity of memory accesses in the index space of arrays



Thank your