RESEARCH ARTICLE

Array relocation approach for radial scanning algorithms on multi-GPU systems: total viewshed problem as a case study

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ABSTRACT
In geographic information systems, Digital Elevation Models (DEMs) are commonly processed using radial scanning based algorithms. These algorithms are particularly popular when calculating parameters whose magnitudes decrease with the distance squared such as those related to radio signals, sound waves, and human eyesight. However, radial scanning algorithms imply a large number of accesses to 2D arrays, which despite being regular, results in poor data locality. This paper proposes a new methodology, termed sDEM, which substantially improves the locality of memory accesses and largely increases the inherent parallelism involved in the computation of radial scanning algorithms. In particular, sDEM applies a data restructuring technique prior to accessing the memory and performing the computation. In order to demonstrate the high efficiency of sDEM, we use the problem of total viewed computation as a case study. Sequential, parallel, single-GPU and multi-GPU implementations are analyzed and compared with the state-of-the-art total viewed computation algorithm. Experiments show that sDEM achieves an acceleration rate of up to 827.3 times for the best multi-GPU execution approach with respect to the best multi-core implementation.

KEYWORDS
Digital Elevation Model (DEM); array relocation; total viewshed map; multi-GPU system; CUDA acceleration

1. Introduction

Algorithms implementing radial scanning study the relationship between a certain point within a particular 2D array and the rest of the values through the application of an azimuthal discretization procedure. This is achieved by considering the study point as the vertex of the array. The Digital Elevation Model (DEM) is divided into angular sectors in the plane, where the axis of each sector completely represents the whole sector. The importance of every axis progressively decreases as we move away from the vertex, since the width of the sector increases linearly with the radius. The required accuracy will also be reduced to the same extent, making this sort of algorithms suitable for addressing some well-known problems.

With respect to viewed computation, the analysis of DEMs from a specific point
located in the terrain itself is a widely studied problem. This reference point is called point of view (POV) and attracts a great deal of interest among researchers. In many situations, the POV works as a transmitter or a receiver of certain signals whose strength decrease with the distance squared, such as radio signals, sound waves, or the sight of an observer at ground level, among others. Indeed, these sorts of problems are characterized by a decrease in the relationship between the POV and the rest of the area as the distance increases. Hence, the required accuracy is lower for the farthest points in the area.

One of the most challenging issues could be related to the computation of the visibility (VS) of an observer located at a certain elevation $h$ with respect to the ground. Most Geographic Information Systems (GIS software), such as ArcGIS ([ESRI] 2010), GRASS GIS (Neteler et al. 2012), or the well-known Google Earth, implement specific modules for viewshed computation, however demonstrate poor performance. Accurate knowledge of the visibility in an area is crucial for different fields of study, such as telecommunications, environmental planning, ecology, tourism, and archaeology. For instance, the development of algorithms which identify the fewest possible number of POVs providing maximum sight for a certain area would be greatly simplified if the visibility of every point in the area is known beforehand ([Franklin and Ray] 1994).

Considering the total viewshed problem as a case study, in this work we propose a new methodology called sDEM (skewed DEM), which performs a prior restructuring of the DEM data in memory before computing the total viewshed. This approach achieves maximum performance through efficient memory accesses. Based on this method, the multi-GPU sDEM+ implementation is presented with the aim of accelerating the calculation of the total viewshed, focusing on fully exploiting the intrinsic parallelism of this particular procedure. This approach can be applied to other problems where the radial scanning method is used to increase the performance of an application.

The remainder of this paper is organized as follows: Section 2 presents the state-of-the-art CPU and GPU algorithms for total viewshed computation. Section 3 explains current GPU hardware and software, with particular focus on the CUDA parallel computing platform. Section 4 reviews the background related to this research. Section 5 explains the proposed sDEM methodology for computing the total viewshed. Section 6 presents the sDEM+ implementation for multi-GPU systems. Section 7 evaluates the proposed algorithm in terms of speed-up and accuracy. Section 8 discusses the results of this study.

2. Related work

Terrain visibility, commonly known as viewshed analysis, is related to the problem of obtaining the area of the terrain visible from a POV located at a certain elevation above the ground. This issue has been widely studied for many years in the literature (Atallah 1983, Cabral et al. 1987, Fisher 1992, Franklin and Ray 1994, Floriani and Magillo 1994) given the mass of interpolation computations required to produce precise results. Authors usually use line of sight (LoS) algorithms such as R3, R2 or DDA (Franklin et al. 1994, Kaučič and Zalík 2002). These methods project rays starting from the observer toward the boundary of the DEM to obtain the points to be considered in the processing. Another strategy based on this methodology is known as XDraw (Franklin et al. 1994) and computes the LoS function in stages arranged as concentric squares centered on the position of the observer.

Many algorithms are developed for calculating the VS parameter from one single
POV, or from a small number of POVs at best. In Gao et al. (2011) a singular viewshed implementation was developed for built-in GPU systems based on the LoS method and texture memory with bilinear interpolation. They achieve a speed-up up to 70 times with respect to the sequential CPU implementation. The GPU implementation proposed by Stojanovic and Stojanovic (2013) achieves remarkable results in obtaining a Boolean raster map instead of a map containing viewshed values. A novel reconfiguration for GPU context of the XDraw algorithm is described in Cauchi-Saunders and Lewis (2015) which outperforms CPU and GPU implementations of well-known viewshed analysis algorithms such as R3, R2, and XDraw. Furthermore, an efficient implementation of the R2 viewshed algorithm is carried out in Osterman et al. (2014) with a focus on input/output efficiency and obtaining significant results in contrast to R3 and R2 sequential CPU implementations. The algorithm described in Zhao et al. (2013) focuses on a two-level spatial domain decomposition method to speed-up data transfers and thus, performs better than other well-known sequential algorithms. Other extended approaches are focused on obtaining the viewshed for multiple points (Strnad 2011, Song et al. 2016).

More recent research is presented in Wang and Dou (2019) where fast candidate viewpoints are obtained for multiple viewshed planning. These authors also present additional papers for parallel XDraw analysis (Dou et al. 2018, 2019) improving the results of previous XDraw algorithms. Additionally, some authors have recently presented related approaches where DEMs are not used for total viewshed calculations, but for flow-routing/watershed calculations (Rueda et al. 2016, Liu et al. 2018, Wu et al. 2019, Stojanovic and Stojanovic 2019). Nevertheless, few studies address the total viewshed computation problem and most of them focus on tackling a simplified version of it. For example, in Dungan et al. (2018) total viewshed is obtained by drastically reducing the number of grid points to be processed. Similarly, the approach used in Brughmans et al. (2018) computes the visibility of small areas and not specific points. So far, the only algorithm that addresses the total viewshed problem on high resolution DEMs is the TVS algorithm proposed by Tabik et al. (2013, 2015).

In this study, we propose computing total viewshed based on a compact and stable data structure with the objective of increasing data and computation reuse, outperforming most commonly used GIS-software. Our proposal will be compared in terms of run-time and accuracy to the TVS algorithm (Tabik et al. 2015).

3. General-purpose computing on GPUs

The role of Graphics Processing Units (GPUs), also known as General-Purpose Computing on Graphics Processing Units (GPGPU), has evolved in the last decade from managing tasks particularly related to visual rendering to more general data processing. Specific applications that need to manage and process a massive amount of data can be remarkably accelerated by using graphical processing units.

The first GPU developers had to express their mathematical problems using vertices and pixels so that they could be executed using GPUs for general-purpose computing. However, it was not until 2006 when NVIDIA launched a hardware and software architecture to use NVIDIA GPUs for that purpose. The framework, known as Compute Unified Device Architecture (CUDA), provides high-level abstraction for C/C++ programming and enables applications running on the CPU (host) to perform data processing on the GPU (device).
3.1. **Hardware and software structure**

NVIDIA CUDA hardware architecture is formed by a set of Stream Multiprocessors (SMs), whose number depends on the GPU architecture. Each SM is normally composed of 32 cores, which can run many threads performing Single Instruction Multiple Data (SIMD) operations. Regarding the CUDA programming model (Figure 1), functions running on the device, commonly known as kernels, are executed in parallel across a 3D set of threads. Threads are grouped into processing structures called warps (typically containing 32 threads each).

To accomplish maximum performance, each thread from a warp should be running the same instruction on different data elements. This avoids thread divergence issues which occur when threads from the same warp take different paths after processing a branch instruction, such as with conditionals and switch statements. At a higher level, threads are also grouped into 2D arrays of thread blocks which run on the same SM, sharing its resources. Finally, thread blocks are gathered together inside a grid and must be able to be executed independently. Communication is not possible between blocks unless the global memory is used, however this results in a significant reduction of performance. We will denote block and thread identification numbers as $b_{id}$ and $t_{id}$, respectively, and thread block dimension as $b_{dim}$ throughout this paper.

3.2. **Memory hierarchy**

According to the device memory hierarchy, the smallest and fastest memory units are registers, followed by local memory, which is much slower. Both types of memory are private for every thread and the data stored cannot be shared between them. The next level of memory is the shared memory space, whose data is accessible for all threads within the same block, provided that the block is being executed. The largest
but slowest storage space is the global memory, which can be accessed by all thread blocks, therefore allowing the sharing of data between threads, even between those that belong to different blocks. This last memory unit is also used for communication with the host unit. Data in the host can be directly allocated in pinned memory, improving transfer speeds by preventing the memory from being swapped out.

4. Background

A common approach applied in most viewshed computation algorithms is performing the azimuthal partition of the area (from a particular POV) prior to executing the radial scanning algorithm. This partition is carried out by splitting the area that surrounds the observer into a number of \( ns \) azimuthal sectors \( s \). For every selected sector, or direction of the axis that passes through the sector, the closest points to the axis are frequently used to represent the entire sector and considered for the viewshed computation.

#### Algorithm 1 Viewshed computation for a chosen POV on a particular DEM

```plaintext
global point POV = DEM[i,j]
POVh += h
float VS = 0
for s = 0, ns/2 do
  pointSet axis = selectAxisPointSet(POV, s)
  VS += linearViewshed(axis, true) // forward
  VS += linearViewshed(axis, false) // backward
end for
VS *= (π/ns) // Papus theorem scaling
```

#### Algorithm 2 linearViewshed(axis, forward)

```plaintext
global bool visible = true
global float maxθ = −∞ // Max. angle
global pointSet visibleSet = emptySet
do
  T = (forward) ? axis.next() : axis.prior()
  pointViewshed(axis.POView,T)
while T != (forward) ? axis.last() : axis.first()
return visibleSet.measure()
```

#### Algorithm 3 pointViewshed(POV,T)

```plaintext
float dist = sqrt((Tx − POVx)² + (Ty − POVy)²)
float θ = (POVh − T_h) / dist
bool prevVisible = visible
if (θ > maxθ) visible = 1
bool startRS = !prevVisible & visible
if (startRS) dist0 = dist
bool endRS = prevVisible & !visible
if (endRS) visibleSet.add(dist, dist0)
```
4.1. Singular viewshed

The calculation of the VS for a chosen POV on a particular DEM, using a regular Cartesian grid, is presented in Algorithm 1 where \( i, j \) and \( \text{POV}_h \) are the coordinates and height of the observation point \( \text{POV} \) (considering the observer is slightly above the ground \( h \)); \( \text{axis} \) is the set of points representing the sector, which are typically close to the axis, and \( \text{selectAxisPointSet} \) function selects the closest points to the axis, which are used to represent the entire sector.

The viewshed, normally considered to be the visible area in a certain sector and for an observer located on the axis of that sector, is obtained by calculating the visibility of every remaining point on the axis. This path is travelled from the nearest point to the furthest point following the corresponding direction. The calculation of the viewshed for a particular point on the axis of a sector is shown in Algorithm 2 and 3 where \( \text{visibleSet} \) corresponds to the set of points on the axis which are visible from the current \( \text{POV} \). The target point \( T \) is visible from the origin point if its angular altitude \( \theta \) is higher than all the previous ones considered in the set (\( \text{max}\theta \)). These points were included in \( \text{axis} \) structure and analyzed in both directions using \( \text{next} \) and \( \text{prior} \) functions until \( \text{last} \) and \( \text{first} \) locations.

The calculation of the visibility for a particular target point \( T \) from a selected \( \text{POV} \) is carried out in Algorithm 3. This last algorithm improves efficiency by measuring only the starting and ending points of a segment (\( \text{visibleSet}.\text{add} \)) in which all the points are visible from \( \text{POV} \), known as visible section or sector rings (shown in Figure 2). Thus, memory accesses and mathematical calculations are reduced by using this method as proven in Tabik et al. (2015). During radial scanning through the axis of the sector, this methodology uses \( \text{startRS} \) and \( \text{endRS} \) variables to indicate whether a sequence of visible points have been found. The distance between the \( \text{POV} \) and the first point found belonging to a visible section is stored in a global variable named \( \text{dist} \). This value is used to obtain the area of the visible section (\( A_{vs} \)) when the final visible point is found with the final distance stored in \( \text{dist} \). Considering a visible section with one degree of opening, the area is obtained as follows:

\[
A_{vs} = \left( \frac{\pi}{360} \right) \cdot (R^2 - r^2)
\]

where \( R \) and \( r \) are the radius of the visible ring sector related to the \( \text{endRS} \) and \( \text{startRS} \) values, respectively, with respect to a particular \( \text{POV} \). The \( \text{visibleSet}.\text{measure} \) results from the addition of every visible section.

Figure 2. Side and zenithal views for a particular \( \text{POV} \), with a specific height \( h \), from which two segments are visible (represented both by blue thick segments). The corresponding visible ring-sectors are obtained for each one.
4.2. Real problem complexity

Radial scanning algorithms can significantly reduce the complexity of the calculations from at least $O(N)$ to $O(s \cdot N^{1/2})$, where $N$ is the size of the 2D array measured in points. Considering that a common DEM widely exceeds several millions of points and the discretization of the sector is rarely above the required accuracy, the accomplished reduction is between one and three orders of magnitude (Stewart 1998). For example, the complexity to obtain the viewshed using point–to–point algorithms such as R3 is $O(N^{3/2})$, whereas it is up to $O(s \cdot N^{1/2})$ for radial scanning methods.

Nevertheless, this continues to be a large number of operations, which makes parallelism and supercomputing highly recommended for these sorts of applications. In fact, one of the problems that was considered unapproachable is related to the total visibility calculation, which is described in detail below.

4.3. Total viewshed

Not long ago, the problem of addressing the viewshed for all points in an area for a particular DEM (with $N$ points of observation) was almost impossible. The reason for this was the fact that the calculation of the VS for a single POV in an area, represented by a few million points, would have been incredibly time-consuming on the CPU.

Considering a DEM represented by a Cartesian grid with a dimension of $dimx$ and $dimy$ points, the problem can be expressed as shown in Algorithm 4, where $TVS$ denotes the total viewshed matrix (with the same dimensions as the DEM) in which the viewshed value is stored for every point, considered as POV within the area. The inherent complexity of the problem is up to $O(N^3)$ since we applied the non-optimized approach $N$ times over a problem of $O(N^2)$ complexity. Nevertheless, using radial discretization, the problem complexity is up to $O(s \cdot N^{3/2})$, proving why these sorts of problems were not addressed a few years ago.

Algorithm 4 Total DEM viewshed computation assuming an observer of $h$ height

```plaintext
for $i = 0, dimy - 1$ do
    for $j = 0, dimx - 1$ do
        $TVS[i, j] = \text{viewshed}(i, j, h)$
    end for
end for
```

4.4. Data reuse in the Band of Sight

In some cases, the line of sight may contain very few or no points. To solve this problem, in Tabik et al. (2015) the closest points to the line of sight are considered into a sample set of points. This structure was named band of sight (BoS) and obtains the total viewshed (stored in the axis structure $\text{selectAxisPointSet}$ shown in Algorithm 1). In this approach however, the distance to the axis depends on the number of points contained in the profile data structure called list and this value determines the number of points in the BoS (Floriani and Magillo 1994). Related algorithms such as the one presented in Franklin and Ray (1994), although similar concepts are applied, use the closest points to the axis, or the points resulting from the interpolation procedure.

Figure 3 shows two particular cases of band of sights with different sizes considering a sector $s = 10^\circ$; only the points of the grid in dark color are considered for the
calculations. The extensive statistical study conducted in Tabik et al. (2015) proves that the size of the structure is not a key factor, as long as it is of the order of \( \sqrt{N} \). Furthermore, most radial scanning studies report that the method used to interpolate DEM data with respect to the axis of the sector is not a determinant factor in the accuracy of the results, consequently from the loss of precision with distance.

The data reuse of the BoS formed by the closest points from the DEM to the sector direction \( \vec{s} \), is the key to achieve proper optimization in total viewshed computation. This is accomplished by reusing the points contained in the list and obtaining the viewshed for every aligned point in the direction of a particular sector and hence, accomplishing maximum memory utilization (Tabik et al. 2015). Nevertheless, this algorithm has important limitations:

- The scanning of the points is performed sequentially because it is not possible to know whether a point is visible or not without knowing the state of the point prior to the latter for a particular POV.
- Its implementation produces an important overhead related to the selection of the points belonging to the BoS for every direction. This overhead will be eliminated using our sDEM methodology.
- It is not appropriate for implementation on high-throughput systems such as GPUs and Xeon-Phi architectures, because parallelism is limited to the sector (hereinafter referred to as sector-parallel).

5. sDEM: a grid reorganization approach

On the basis of the intrinsic parallelism of the total viewshed computation problem, we developed our proposed algorithm considering the technical features of CPU (host) and GPU (device) processing units to take full advantage of these high-performance devices. We will reference our proposal as sDEM throughout this paper.

5.1. Proposed methodology

Complete relocation of the data is performed prior to computation, allowing for the exploitation of the existing parallelism without adversely affecting the precision of the results, based on the following statements:

- The use of the Stewart sweep method (Stewart 1998) which places the loop that runs through the sectors first, as this is the only model that guarantees the reuse of data aligned in one particular direction.
• Given a direction of the sector, all the bands of visibility which cross the DEM in parallel are built simultaneously. This implies the creation of a new DEM of the area that, through the different lengths of the bands, would have a more or less biased aspect.
• Simplify the interpolation method for the calculation of parallel bands based on Bresenham’s algorithm, which is commonly used for line rasterization. This was chosen for its high speed as well as maintaining sufficient fidelity to the problem under consideration (which does not require great precision in distance).
• Propose a compaction scheme of the data especially appropriate for processing on the GPU. This scheme aims at reducing the conditional structures to the maximum, hence avoiding the well-known thread divergence penalty.

The pseudo-code for computing the total viewshed resulting from the array relocation method is presented in Algorithm 5. The skew function reorganizes the data of the DEM into a new matrix called skwDEM according to the chosen sector s, where k is a constant value for every sector which corrects the deformation of the digital skewed model. For the sake of simplicity, although in Algorithm 5 the limit of the loop that runs through the rows of the skewed structure has a value of $\sqrt{N}$, in practice, this range changes based on the bands of values presented in Table 1.

To illustrate the proposed method visually, Figure 4 shows the different possible redistributions of rows and columns of the DEM of the Montes de Malaga Natural Park (Malaga, Spain). In this example, we will assume that the data of the same latitudes are stored contiguously in memory; that is, the external loop runs from north to south, whereas the internal loop runs from west to east over the selected DEM shown in Figure 4(a). In Figure 4(b) the skewed model (termed skwDEM structure) is graphically represented. Using the interpolation, all parallel segments from Figure 4(a) were projected into Figure 4(b) so that the size of both structures matches (the number of non-null elements). In the new reorganized dataset, unlike the original, all the data in the particular search direction is placed in the same row and therefore, memory accesses are sequentially performed increasing locality.

| Minimum angle | Maximum angle | Lower limit | Upper limit |
|---------------|--------------|-------------|-------------|
| 0°            | 45°          | dimx        | dimx + dimy |
| 45°           | 90°          | dimx + dimy | dimy        |
| 90°           | 135°         | dimy        | dimy + dimx |
| 135°          | 180°         | dimy + dimx | dimx        |

**Algorithm 5 sDEm algorithm for total viewshed computation using array relocation**

```plaintext
float VS = 0
for s = 0, ns/2 do
  float sectorVS = 0
  skwDEM = skew(DEM, s) // Rewrite DEM
  for i = 0, $\sqrt{N}$ − 1 do
    sectorVS += linearViewshed(i, true)
    sectorVS += linearViewshed(i, false)
  end for
  // Skewing and Papus theorem scaling:
  VS += (k · ($\pi$/ns) · sectorVS)
end for
```
This new reorganized matrix could later be compacted in two ways: moving all the data from the skewed matrix to the first column of the matrix as shown in Figure 4(c), or relocating the data in another column as displayed in Figure 4(d). This last method aims to further compact the information by eliminating and relocating it to the area in light color below the triangle. Although the approaches shown in Figure 4(c) and Figure 4(d) seem to fit better for GPU processing in theory, several experiments carried out have not revealed significant differences and therefore, the simplest and fastest approach shown in Figure 4(b) will be used for our implementations.

6. sDEM+: multi-GPU implementation

Since this particular problem is similar to matrix processing, our proposal to accelerate the calculation of the total viewshed focuses on exploiting the intrinsic parallelism of this procedure through the use of GPU processing units. Our multi-GPU implementation will be denoted as sDEM+ throughout this paper, or more precisely sDEM+D where D indicates the number of GPUs used in the experiments.

Regarding the implementation details, each available device sequentially launches three different kernels to process the viewshed for every chosen direction. Therefore, through repeating these steps for every remaining direction, we obtain the accumulate results of the total viewshed for every point located on the map.

The first step is allocating the necessary vectors in both host pinned-memory and device memory so that the DEM matrix of $\text{dim}_y \cdot \text{dim}_x$ size can be transferred from host to device using the most efficient strategy, preventing the memory from being swapped out. Memory spaces for $\text{skwDEM}$ and $\text{skwVS}$ matrices of size $2 \cdot \text{dim}_y \cdot \text{dim}_x$ and VS matrix of the same size as the DEM structure are allocated in device memory. The skwVS matrix stores the viewshed for every point located on the skewed DEM in the device memory and hence, a transformation is necessary to store these values in the corresponding locations within the original VS structure at the end of the procedure. This method is used to avoid dependencies between threads while performing the viewshed computation. Moreover, the necessary host memory space is also allocated to store the final total viewshed values transferred from the device after computation.
6.1. **Kernel-1: obtaining the skewed DEM**

This kernel is in charge of transforming the original DEM into a skewed DEM for a particular direction (Algorithm 6). In this new model and for the chosen direction, points located consecutively in the terrain are also stored sequentially in memory, which improves the performance of the memory accesses. Interpolation based on Bresenham’s algorithm is used to soften the projection of the points. This kernel is launched using $C_{by} = \text{dimy}/8$ and $C_{bx} = \text{dimx}/8$ 2D threads blocks with 8 threads per block, so as not to exceed the maximum register file size shared between thread blocks, avoiding schedule problems.

**Algorithm 6** The kernel in charge of generating the $skwDEM$ structure from the $DEM$ given direction $s$

\[
\text{int } i = \text{idy} \cdot \text{dimy} + t_{idy} \\
\text{int } j = \text{idx} \cdot \text{dimx} + t_{idx} \\
\text{float } y = \tan(s) \cdot j \\
\text{int } dest = y \\
\text{float } r = y - dest \\
\text{int } p = \text{dimy} + i - dest \\
\text{if } i < \text{dimy} \&\& j < \text{dimx} \text{ then} \\
\text{skwDEM}[p][j] += (1 - r) \cdot \text{DEM}[i][j] \\
\text{skwDEM}[p-1][j] += r \cdot \text{DEM}[i][j] \\
\text{end if}
\]

6.2. **Kernel-2: viewshed computation on the skewed DEM**

This kernel computes the viewshed for a given direction and every point located in the $skwDEM$, obtaining as a result the $skwVS$ matrix. The pseudo-codes of this kernel are shown in Algorithms 7 and 8, where each thread manages a particular point $POV_t \in skwDEM, t = \{i,j\}$ considering $t$ as the corresponding two dimensional thread. The variable $h$ contains both the observer and location heights. Every thread obtains its computation range of non-zero values within the corresponding row (contained in the nzSet structure) from the $skwDEM$ matrix. Then, every thread computes its visibility forward and backward across the row to which it belongs. The resulting viewshed value is thereafter stored in its corresponding position of the $skwVS$ matrix. This kernel is launched with $2 \cdot C_{by}$ and $C_{bx}$ 2D threads blocks using twice as many thread blocks as in the y-dimension because the $skwDEM$ has twice the y-dimension in that direction.

**Algorithm 7** The kernel in charge of the $skwVS$ computation on the skewed DEM

\[
\text{int } i = \text{idy} \cdot \text{dimy} + t_{idy} \\
\text{int } j = \text{idx} \cdot \text{dimx} + t_{idx} \\
\text{float } r = (1.0/\cos(s))^2 \\
\text{float } cv = 0 \\
\text{if } i < 2 \cdot \text{dimy} \&\& j < \text{dimx} \text{ then} \\
\text{float } h += sDEM[i][j] \\
\text{cv += linearViewshed(i, j, h, skwDEM, true)} \\
\text{cv += linearViewshed(i, j, h, skwDEM, false)} \\
\text{skwVS[i][j] = cv \cdot r} \\
\text{end if}
\]
Algorithm 8 linearViewshed\((i, j, h, \text{skwDEM}, \text{forward})\)

```plaintext
int k = j
int dir = 0
if (forward) then dir = 1 otherwise dir = -1
bool visible, above, opening, closing
float maxθ = -∞
while \(k \in \text{nzSet}\) do
    \(Δd = |k - j|\)
    \(θ = (\text{skwDEM}[i][k] - h)/Δd\)
    if (\(θ > maxθ\)) then above = 1
    opening = above & !visible
    closing = !above & visible
    visible = above
    \(maxθ = \max(θ, maxθ)\)
    if (opening) then open\(Δd = Δd\)
    if (closing) then \(cv += Δd \cdot Δd - open\Δd \cdot open\Δd\)
    \(k += \text{dir}\)
end while
```

6.3. **Kernel-3: obtaining the final viewshed on the DEM**

Once the viewshed is computed on the \(\text{skwDEM}\) for every POV and stored in the \(\text{skwVS}\), this kernel transforms this last structure by undoing the rotation performed in Kernel-1 to obtain the final viewshed \(\text{VS}\) matrix on the original DEM. The pseudocode in charge of performing this procedure is presented in Algorithm 9. This kernel is also launched with the same configuration as Kernel-1.

Algorithm 9 The kernel in charge of transforming the \(\text{skwVS}\) on the skewed DEM to the \(\text{VS}\) structure on the original DEM

```plaintext
int i = \(b_{idy} \cdot b_{dim} + t_{idy}\)
int j = \(b_{idx} \cdot b_{dim} + t_{idx}\)
float y = \(\tan(s) \cdot j\)
int dest = y
float r = y - dest
int p = \(\text{dimy} + i - dest\)
if \(i < \text{dimy} \& \& j < \text{dimx}\) then
    float \(\text{skwVS}_a = \text{skwVS}[p][j]\)
    float \(\text{skwVS}_b = \text{skwVS}[p-1][j]\)
    \(\text{VS}[i][j] += (1 - r) \cdot \text{skwVS}_a + r \cdot \text{skwVS}_b\)
end if
```

6.4. **Scheduling multi-GPU processing on the host**

In order to perform the total viewshed calculation in a multi-GPU system, several steps must be performed as shown in Algorithm 10. First, memory spaces which store the different matrices in every device memory must be reserved, and then the \(\text{DEM}\) structure can be transferred from the host to each device \(\text{Dev}\) of the total available \(n\text{Dev}\). Every direction from the target number of sectors \(ns\) will be distributed among the different devices so that the work load is balanced. Each device will accumulate every singular viewshed result in their private \(\text{VS}_t\) structure. Finally, these matrices are transferred from the devices to the host so that a final parallel reduction can be performed on the last one, obtaining the final total viewshed \(\text{VS}\) result.
Algorithm 10 Host code in charge of scheduling the work for the different devices

for \( t = 0, nDev \) do
    \( \text{Dev}_t \leftarrow \text{Allocate}(\|DEM\|, |skwDEM|, |skwVS|, |VS|) \)
end for

for \( t = 0, nDev \) do
    \( \text{Dev}_t \leftarrow \text{MemcpyAsyncH2D}(DEM) \)
end for

for \( s = 0, ns \) do
    int \( t = s \% nDev \)
    \( \text{Dev}_t \leftarrow \text{Kernel} - 1, 2, 3 \)
    \( \text{Dev}_t \leftarrow \text{MemcpyAsyncD2H}(VS_t) \)
end for

for \( t = 0, nDev \) parallel do
    \( VS += VS_t \)
end for

7. Experiments

We carried out two experiments to analyze the performance of the new sDEM algorithm with respect to the TVS algorithm proposed in Tabik et al. (2015) considering the total viewshed problem as a case study:

- E-1: Sector viewshed calculation for a random direction, sector of 10° is selected.
- E-2: Sector viewshed computation considering directions from 0° to 45°, for the sake of simplicity, to obtain mean values per sector.

Our experiments were executed on a system with an Intel(R) Xeon(R) CPU E5-2698 v3 @2.30GHz with 16 cores (32 threads) and 256GB DDR4 RAM, along with four GTX 980 Maxwell GPUs with 2048 CUDA cores, 16 SMs, 1.12GHz, and 4GB GDDR5 each one. The OpenMP API is used to enable the multi-threaded execution of every selected sector with dynamic scheduling since it has proved to obtain the best performance. Host codes are compiled using the g++ open-source compiler with optimization flags, while CUDA files make use of the NVIDIA NVCC compiler.

The experiments were designed to be as representative as possible of a real problem where obtaining the visibility in a particular direction or region is necessary. This is the reason why three DEMs of the Montes de Malaga Natural Park with 10 meters of precision and different dimensions, in relation to the number of points in vertical and horizontal directions, were considered and whose characteristics are presented in Table 2. The calculation of the total viewshed is not only limited to this area of interest, but includes the surrounding area beyond it. This area is very geographically diverse, as it contains very flat areas, along with others which are very mountainous and steep. Observers are considered to be located 1.5 meters above the ground. The direction range is selected up to 45° since results within this range are representative and can be extrapolated to any target range, considering that sector-parallel executions

| UTM     | Dataset Dimension | Easting | Northing |
|---------|-------------------|---------|----------|
|         | Z               | EA      | NA       |
| DEM10m-2k | 2000x2000        | 30S     | 0310000mE | 4070000mN    |
| DEM10m-4k | 4000x4000        | 30S     | 0360000mE | 4100000mN    |
| DEM10m-8k | 8000x8000        | 30S     | 0390000mE | 4140000mN    |
of TVS and sDEM required several weeks to complete. The sector-parallel version of the TVS algorithm is compared to both sector-parallel (sDEMs) and full parallel (sDEMp) implementations of our proposal developed for CPU processing, along with the single-GPU (sDEM+1) and multi-GPU (sDEM+2 and sDEM+4) implementations of the sDEM algorithm. We are not considering other algorithms from the literature apart from TVS since it is the only one performing the total viewshed computation on entire datasets without carrying out prior reductions in workload. In the case of the TVS algorithm, a size of $\text{dim}_x$ has been chosen for the band, so that the BoS structure coincides with the number of points processed per row in our proposed algorithm. Thus, the workload is similar for both TVS and sDEM algorithms making it possible to perform a comparison study in terms of run-time (including memory transfers and data allocation time expenses on the devices) and accuracy.

Figures 5 and 6 present the acceleration curves and the throughput results (POVs processed per second) for our different sDEM implementations for first and second experiments, respectively. The parallel implementation of our proposal is launched

![Figure 5](image1.png)

**Figure 5.** Speed-up curves and throughput diagrams for the TVS algorithm and our different proposed implementations in computing singular viewshed for the random $s = 10^6$ direction (E-1 with BoS size of $\text{dim}_x$ points per sector). Every color is related to a particular dataset. Logarithmic scale is used.

![Figure 6](image2.png)

**Figure 6.** Speed-up curves and throughput diagrams for the TVS algorithm and our different proposed implementations in computing sector viewshed considering directions fulfilling $0^\circ < s < 45^\circ$ to obtain mean values per sector (E-2 with BoS size of $\text{dim}_x$ points per sector). Every color is related to a particular dataset. Logarithmic scale is used.
with the maximum number of threads available in the system, the same way that GPU implementations are configured to operate the devices at full capacity. Results show that:

- **E-1**: Our proposal outperforms the TVS algorithm achieving a maximum acceleration up to 232.8x using the sDEM+1 implementation on DEM10m-4k. Throughput results show that this variable increases about 177.7x for that implementation on DEM10m-2k. sDEM+2 and sDEM+4 implementations are not considered due to the low workload when distributing it among more than one device.
- **E-2**: The maximum speed-up result achieved is up to 827.3x with the sDEM+4 implementation with respect to the TVS algorithm considering DEM10m-4k. Throughput results show that this variable increases about 511.1x for that implementation on DEM10m-2k.

The final outcome from computing our proposed sDEM algorithm to obtain the total viewshed map of the Montes de Malaga Natural Park (Malaga, Spain) is presented in Figure 7. No substantial differences have been found after analyzing the values of absolute and relative differences when comparing accuracy results of the total viewshed outcomes from the TVS and sDEM algorithms. The DEM10m-2k was used for this analysis, where the maximum absolute difference found is up to 1.18% for the sDEM+4 implementation, whereas the maximum relative difference is up to 4.21% for the same version. All these values are fully within the limits recommended by several researchers in this field (Tabik et al., 2013).

![Figure 7. Total viewshed map of the Montes de Malaga Natural Park and its surroundings in the province of Malaga, Spain.](image)
8. Conclusions

In this paper, we present a new technique called sDEM to speed-up algorithms using the radial scanning method. Total viewshed computation was selected as a case study to analyze the performance of this new methodology. This algorithm was designed from scratch and differs from state-of-the-art methods in the way that operations are performed. It focuses on increasing the performance of memory accesses by applying a data restructuring before starting the computation. The proposed data reorganization opens the door for intensive use of GPUs in many algorithms for which it had never been considered because of their irregularity and low efficiency.

Different versions of our algorithm have been proposed including sector-parallel, full parallel, single-GPU and multi-GPU (sDEM+) implementations, along with intensive studies of their performance compared to the best ever state-of-the-art algorithm for total viewshed computation. Our implementations have proved to largely outperform the TVS algorithm considering both speed-up and throughput results for every studied DEM in two experiments. Our approach accelerates the total viewshed calculation up to 827.3 times for the best studied case with respect to the baseline multi-core implementation on a DEM formed by 16 million points of view.

Our algorithm can be used for analyzing any terrain in terms of generating the visibility map in considerably reduced time in comparison with the algorithms reported in the literature. Once this paper is accepted, we will release a plug-in so that the international scientific community can reproduce our experiments with the sDEM algorithm and use it with their own datasets to obtain total viewshed maps.

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