A GPU accelerated implementation of DFT for hybrid QM/MM simulations.

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Abstract

This paper presents an implementation of electronic structure calculations based on density functional theory (DFT). This development is optimized for performing hybrid molecular dynamics simulations (QM / MM) by making use of graphic processors (GPU) for the most computationally demanding parts. The proposed implementation is able to make use of modern GPUs and to achieve accelerated calculation in relevant portions between 20 to 10 times faster than the CPU version, even in small quantum systems. Besides, we introduce other minor optimizations that significantly reduce the initialization time and the number of iterations required for convergence, which is especially important in molecular dynamics (in which thousands or millions of calculations on small systems are performed). The presented code was extensively tested, both in terms of numerical quality and performance over systems of different size and composition.

1 Introduction

The simulation of chemical properties in complex systems (solution, proteins, etc.) with electronic detail generally requires treatment by means of computationally expensive methods. One approach is to treat these systems using hybrid

(QM/MM) methods. In this approach the system is divided into a subsystem treated with a Hamiltonian based on quantum mechanics while the rest is modeled with a classical Hamiltonian. This methodology allows for the treataments of complex systems with many degrees of freedom. However, the computational cost associated with the resolution the self-consistent electronic problem remains a major constraint when applying this type of model.

On the other hand, given the immense computing capabilities of the current graphics processing units (GPU), these appear as attractive alternatives in the area of high-performance computing. In particular, the use of GPUs in quantumchemistry has allowed to obtain interesting results. There are several works that employ GPUs in diverse electronic-structure calculations ^{1–7}, and there's even a commercial software developed exclusively for this kind of hardware⁸. A particularly relevant work is Yasuda's⁹, in which an algorithm for the exchange-correlation calculations related to self-consistent field iterations (SCF) is presented. It is important to take into consideration that the possibility of obtaining efficient algorithms depends strongly, aside from the hardware to be used, on the type of systems that have to be solved (size, type of atoms, basis-functions, etc.).

In our case, it is of great interest the use of hybrid simulation techniques (QM/MM) to study biomolecules active sites: the presented implementation is oriented towards these systems, which usually are not bigger than 50 or 100 atoms and which may include relatively heavy elements such

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as Iron, Sulfur, Copper, etc. ^{10–17}. Molecular dynamics simulations involve performing complete DFT calculations a large number of times, each with only a few iterations. This implies that the initialization time has a greater relative weight in this kind of calculation than in a single-point SCF computation.

In summary, we propose a GPU implementation oriented towards QM/MM molecular dynamics calculations of the most computationally demanding steps of a DFT, with Gaussian basis, calculation. This work is based on the code Molecole ¹⁸ and include novel approaches having a positive impact on parallelization and performance without affecting numerical quality. One of these differences consists in including a new partitioning strategy for the set of quadrature points, which results in a more efficient grouping of computational batches in terms of performance and significative functions. Another aspect involves using a low-cost classification criteria for determining these significative functions, which does not require computing the actual function values. While other implementations ¹⁹ proposed the recalculation of function values several times at each iteration, in our implementation we precompute these, obtaining notable performance improvements.

A CPU implementation was also developed and compared to the GPU version. The CPU version is not simply a translation of the GPU implementation since specific CPU features (like SSE2 instructions) were used to obtain the best performance possible. Finally, we present and test a hybrid code made by the coupling of our DFT implementation with AMBER 11²⁰.

2 Method

In the DFT approach, the energy is written as a functional of the density:

$$E[\rho] = T_s[\rho] + V_{ne}[\rho] + \frac{1}{2} \int \int \frac{\rho(\vec{r}_1)\rho(\vec{r}_2)}{r_{12}} d\vec{r}_1 d\vec{r}_2 + E_{xc}[\rho]$$
(1)

where the first term is the kinetic energy associated with the density, the second is the interaction between the density and the nuclei, the third one is the Coulombs repulsion of the density with it-

self and the last is the exchange and correlation energy ²¹.

The global exchange-correlation portion is the most expensive in terms of computational cost. The energy corresponding is calculated by the integral of the local exchange-correlation energy as:

$$E_{XC} = \int \rho(r) \varepsilon_{xc}(\rho(r)) dr \qquad (2)$$

Equation [2] can be computed as a discrete sum over a grid 22 :

$$E_{XC} \cong \sum_{j} \rho(r_j) \varepsilon_{xc}(\rho(r_j))$$
 (3)

where the density ρ (and its gradient, for GGA functionals) over each grid point j is calculated from the molecular orbitals ψ_i as:

$$\rho(r_j) = \sum_{i} |\psi_i(r_j)|^2 \tag{4}$$

with

$$\psi_i(x, y, z) = \sum_{k=1}^n c_i^k \chi_k \tag{5}$$

where c_i are the variational coefficients, and the orbitals ψ_i are constructed by expanding them in a basis of contracted Cartesian Gaussian functions as:

$$\chi_k = (x - x_0)^{n_x^k} (y - y_0)^{n_y^k} (z - z_0)^{n_z^k} \sum_j k_j^k e^{-\alpha_j (\vec{r} - \vec{r_0})^2}$$
(6)

where

$$(\vec{r} - \vec{r_0})^2 = (x - x_0)^2 + (y - y_0)^2 + (z - z_0)^2$$
 (7)

The computation of the exchange and correlation energy (and the corresponding Khon-Sham matrix elements) involves several distinct steps, for all of which a linear-scaling algorithm exists. Still, all steps exhibit a degree of parallelism inherent to their mathematical formulation. Exploiting this aspect gives a great advantage over serial calculations. Nevertheless, there is not a definitive parallel implementation known a priory since the computation can be approached in different ways. One possible solution consists in parallelizing these steps independently and determining the most adequate parallelization strategy for

each case. The main computational steps are: (a) quadrature-point positions and weights, (b) function values, (c) density at each point and (d) Kohn-Sham matrix elements.

To achieve a linear-scaling implementation, Stratman et al propose several strategies²³. As a whole, the main idea consists in grouping quadrature-points instead of solving the computation for each one. This grouping permits determining which basis-functions have a signification contribution to the final computation, which are referred to as significative functions. Given the rapid-decay of Gaussian functions, the size of the set of significative functions associated with each group of quadrature points does not depend on the number of atoms. In other words, this size is of constant order in terms of computational complexity. As a consequence, it is possible to sub-divide the complete DFT calculation by computing each of these groups independently.

2.1 The grid

An important aspect of the calculation is the shape of the grid on which Equation 3 is applied. The usual practice is to generate a grid for the molecule via atomic overlapping grids. These atomic grids come from the superposition of layers derived by scaling a reference layer (see Figure 1).

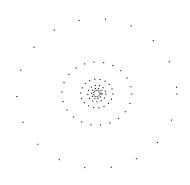


Figure 1: Schematic atomic grid

These layers are not equidistant but are most concentrated close to the nuclei (see Figure 2), where the electron density changes more abruptly, and are more spaced away from them. In a molecule the overlap of atomic grids causes that the relative weight of a given point depends on

the position of the grid points from other atoms, making the calculation scale, in principle, quadratically ²². However algorithms that scale linearly have been developed. ²³

2.2 Partitioning and function selection criteria

The simplest partitioning scheme consists of dividing the whole system volume into fixed-size cubes, therefore grouping neighboring points. However, the distribution of points in space is not homogeneous as a result of the shape of the grid, which concentrates a large number of points near the nuclei where the electronic density changes faster (see Figure 2).

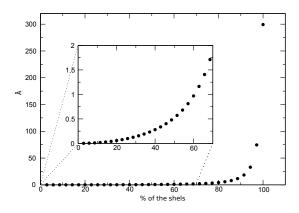


Figure 2: Radii in Angstroms of the grid layers for the oxygen atom.

Therefore, a regular partitioning scheme results in an uneven distribution of points inside groups. Furthermore, points near nuclei share a great number of significative functions, in contrast to points located elsewhere.

Taking into account the previous facts, a hybrid partitioning scheme is proposed in this work. First, a spherical group type is introduced. These spheres are centered around each atom in order to group a given percentage of its concentric grid shells. Then, after excluding these already grouped points from the complete point cloud, the traditional cube-based partitioning is applied. With this hybrid partitioning, the cube sizes can be incremented, therefore producing fewer groups.

The result of this partitioning scheme is a more homogeneous distribution of points and a more appropriate grouping of points in terms of common significative functions (see Figure 3).

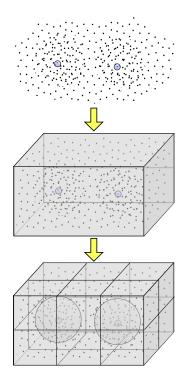


Figure 3: Schematic grid partition

Another aspect that was implemented in this work consists of a simpler selection criteria for significative functions. Independently of the shape of a group, the selection criteria determines which functions are to be computed over the contained points. A simple criterion can consist of determining, for each basis function, if the value over that point is greater than a specific threshold δ . However, this gives the partitioning and selection criterion a considerable computational cost, since it has to be applied to all points of all groups. Even further, the cost of computing a basis-function value is not negligible since it involves calculating various Gaussian functions.

The proposed selection criterion is based on finding a distance of influence for each Gaussian function. Outside this radius of influence the function has a negligible value (lower than a parameter: e^{δ}). The distance between the Gaussian function center and the group (not the points in the group) is calculated and if the function has a radius of influence larger than this distance the function is not used for this group.

As defined, this condition simplifies the computation by not requiring the actual function value on every point in the group. It should be noted that the inclusion condition is only sufficient and not necessary. This means that basis functions not meeting the exclusion criteria could still contribute a negligible value to the calculation, but the amount of these cases will not dominate the resulting computational cost.

As a consequence, with this selection method the computation time for an iteration can be slightly higher than with a more rigorous method but the grid generation time is considerable lower.

2.3 Computation kernels

To parallelize the exchange-correlation calculation, each of the previously mentioned sub-steps is computed by a separate computational kernel, solving each group of points in turn.

During group partition, the point positions have to be computed in order to determine in which group they will be contained. After the partition is obtained, the list of signficative functions of each group is computed. These steps are computed in the CPU, since the corresponding execution time is negligible in both cases. Finally, the weights of the grid points are computed by a GPU kernel, since this is the heaviest computational portion of the partitioning step. This kernel maps one thread to one grid point. Shared memory is used as a cache, to store the atom positions and other relevant parameters.

The second step involves computing the function values. Again, one thread is mapped to a single grid point. The necessary Gaussian parameters are first loaded into shared memory since these do not depend on the grid point position. The function values and their first and second derivatives are all stored in GPU memory in order to be used during the remaining steps of the calculation over this group. When the next group of points is computed this memory is discarded. This approach falls between a fully caching algorithm, where all functions are precalculated and stored for all groups, and a fully recalculating algorithm, where none of the function values are stored but are computed on demand during every iteration. This latter approach corresponds to Yasuda's work⁹, where it was shown that the raw processing power of GPUs could be applied in such way to gain significant performance improvements. In our case, we took advantage of newer GPU architectures which feature faster memory access by including a hierarchical cache, and increased memory capacity.

The next step of the algorithm consists in computing the Kohn-Sham matrix, which is necessary during convergence of the main SCF algorithm. This parallelization strategy used for this kernel differs from the rest in that a bi-dimensional grid of threads is used, where each thread with id $t_{i,j}$ is mapped to the (i,j) element of the matrix. Since the matrix is symmetric, half of these threads would remain idle in principle. However, since the computation is actually subdivided in blocks of threads, blocks completely contained in the lower-left triangle of the matrix are discarded without computational cost. For the blocks laying over the matrix diagonal, dummy computation is performed for the unnecessary thread in order to minimize branch-divergence by using conditional computation. Since each thread will then be responsible of computing the product of functions i, j, it can be seen that each block of threads actually accesses the same range of functions $i_{a..b}$ and $j_{c..d}$.

Therefore, for each block of threads, shared memory is used to first load these two ranges of function values, to be later accessed by all threads in the block. In fact, when caching these functions, values associated with several points are loaded instead of just one. In this way, the computation is performed for batches of points.

Finally, to compute this matrix, the exchange-correlation potential is also needed, therefore another kernel is used for this step. Once convergence is reached, this second kernel computes the final exchange-correlation energy since the calculations are mostly the same. Once again, this kernel maps one thread to one grid point. In this case, the necessary elements of the Kohn-Sham matrix are efficiently loaded into shared memory in order to reduce memory accesses. Since the whole matrix can't possibly fit into shared memory, the computation is performed in batches of fixed size, loading sub-portions of the matrix in turns. This kernel computes the exchange and correlation potentials. Since precision in this steps is of great im-

portance (mainly for the GGA based calculations), double-precision variables are used internally for the two cases. The rest of the GPU kernels can use single-precision variables without significative impact on the final result.

2.4 The Coulomb Integrals.

Another highly demanding part of the electronic-structure calculations corresponds to the Coulomb integrals, which account for the repulsive interaction between electrons (ERIs, third term in equation 1). Previous works have proposed the use of GPU for computing these integrals ^{1,3}. However, in medium size systems, ERIs can be stored in RAM memory, making the calculation time of this term well below of the exchange and correlation. Therefore in our code this contribution is calculated by the CPU and stored in main memory.

Although this integral depends in principle on four centers, which would imply a complexity of $O(n^4)$, it can be easily transformed into an $O(n^2)$ implementation. In particular, we use two approaches in order to accelerate this calculation. The first consists in re-writing the density as a linear combination of Gaussian functions (instead of a product of Gaussians) by employing auxiliary basis-functions to such effect. This reduces an order of magnitude the complexity, while also reducing the pre-exponential factor, given that the number of necessary functions is much lower, in general, than the number of products associated with the original basis. Another approach to reduce the complexity without compromising the numerical quality consists in employing the Gaussian Product Theorem²³ for discarding negligible terms. By employing both techniques a great reduction in the number of terms to compute is obtained, thus allowing to precompute and store these in RAM memory (for example, the Valinomycin $(C_{54}N_6H_{90}O_{18})$ with the 6-31G basis uses only 2 Gb of memory for this). With these approximations the time consumed by this portion of the calculation is drastically reduced resulting considerable less than the time involved in the exchangecorrelation integral computation, at least for systems of interest in this work.

2.5 QM/MM implementation

The DFT GPU based code developed in our group was coupled with the AMBER 11 molecular dynamics package. The periodic boundary conditions were treated with a simple cut-off scheme. Minor changes on the AMBER code were performed, in particular the possibility of uncoupling the temperature control for the QM and MM subsystems and the cut off criteria based on charge groups instead of atoms (only for water molecules).

An additional optimization for molecular dynamics, is the construction of a better initial guess for the density matrix. In a quantum calculation the SCF iteration cycle begins with an initial density matrix. In the context of a molecular dynamics simulation, the naive solution is to use the density matrix converged in the former step. This is a good initial guess, but can be improved if we use the three former density matrices and adopt a quadratic extrapolation scheme to predict the density matrix on the current step. This technique decreases the number of iterations in the SCF procedure required to achieve convergence. In Figure 4 we show the number of SCF iterations vs dynamics step for the naive and the quadratic extrapolation approaches for a system composed of a quantum N-methylacetamide (NMA) in a periodic box of 550 TIP3P water molecules (included in the OM/MM section of AMBER tutorial). The base used in this case is DZVP.

3 Results

Two main aspects are analyzed in the present implementation: performance and numerical quality. In terms of performance, the scalability of the exchange-correlation computation, the overall DFT iteration and grid generation times are analyzed. Comparisons were performed between GPU and CPU implementations and also with other relevant software.

The CPU and GPU implementations were compared over three different systems of moderate size: Taxol ($C_{47}H_{51}NO_{14}$), Valinomycin ($C_{54}H_{90}N_6O_{18}$) and a heme group without any lateral chains, and bound to carbon monoxide (FeC₂₃N₆H₁₆CO), see Figure 5. The former two

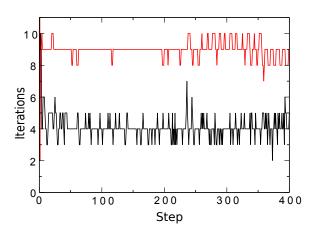


Figure 4: Number of iterations to achieve convergence for a quantum N-methylacetamide (NMA) in a periodic box of TIP3P waters molecules for the naive (red line) and the quadratic extrapolation (black line).

molecules are commonly used in performance measurements ^{9,24}, and the latter is a typical example of a system that is studied with hybrid techniques ^{10,13}. For the Heme group we employs the DZVP basis set, while for the other two systems we use a 6-31G basis set. The auxiliary basis set is a DGA1 in all cases. Computations were performed using the high-density grid (194 angular points and 30 to 35 shells). Optimal parameters were determined as in the previous tests. The PBE ²⁵ functional was adopted for all the calculations.

3.1 Technical details

The graphical processor used for the tests is a NVIDIA GeForce 580GTX, implementing the Fermi architecture and 1.5Gb of DDR2 graphical memory. This GPU was installed on a desktop PC with an Intel Core 2 Quad (Q8200) processor of 2.33Ghz and 4GB of RAM memory.

The GPU code uses NVIDIA's computing interface named CUDA (Compute Unified Device Architecture). Version 3.2 of both the toolkit (which includes the necessary run time libraries and compiler) and GPU driver was used.

In order to obtain a fair analysis, the GPU implementation running on this hardware was compared to a CPU-based implementation running on a HPC Dell Cluster compute node, which features a dual-

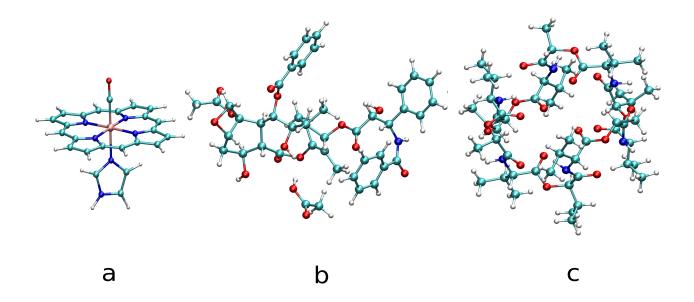


Figure 5: a) Heme, b) Taxol, c) Valinomycin

processor motherboard, with two quad-core Intel Xeon E5410 CPUs running at 2.33Ghz, and 8Gb of RAM. The CPU implementation was compiled using Intel's C/C++ compiler version 11.

Both implementations were specifically optimized for the corresponding hardware. In the case of the CPU version, even while it consisted of a serial version, Intel's fvec library was used in order to produce SSE2 instructions for of the mathematical computations.

Also, on both implementations the parallelized version of Intel's MKL libraries was used for certain steps that are always solved with the CPU (like matrix diagonalization). The usage of these libraries and the presence of eight CPU cores allowed to reduce CPU computation time. This implies that with the GPU version, the GPU accelerated steps conform most of the total iteration time (between 60% and 80% approximately).

3.2 Numerical Quality

Given that the performance of the computation depends on a number of parameters, we first determined the exponent threshold δ by fixing the other two (the size of the cubes and radius of spheres used to partition the system) since they don't affect the overall numerical quality in significative amounts. To maximize both performance and nu-

merical quality, the lowest δ minimizing the error of the final energy is sough. For this purpose, we calculated the error in the energy of formation of a cluster of 24 water molecules:

$$\Delta E = E((H_2O)_{24}) - 24 \times E(H_2O)$$

The value obtained without discarding any function and using only double precision is taken as the reference. In Figure 6 we show the error vs. δ for the CPU and GPU codes, and double and single precision.

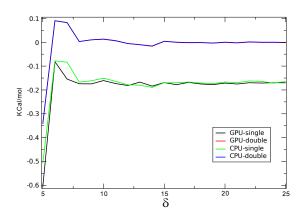


Figure 6: Error in the calculation of the energy of formation of $(H_2O)_{24}$

In Figure 6 it can be seen that both implementations with double precision are equivalent. Ap-

plications that use single precision in certain parts of the calculation achieve similar results, the differences with respect to the full double precision results being less than 0,2 Kcal/mol

With these tests a value of $\delta = 8$ was chosen, given that with higher values the difference in the final energy is lower than 0.02 Kcal/mol in the systems analyzed.

Once δ was determined, for the performance analysis presented in later sections of this work, we performed an exhaustive search of values for the remaining two parameters (between a reasonably wide range), by measuring exchange-correlation calculation time and storing the combination that resulting in the lowest time.

In the following the effect of the use of single precision over the total energy is analyzed. Table 1 shows the energy for some benchmark molecules with the GGA-PBE functional calculated with the full double precision and the single-precision GPU code. The differences are in all cases under one kcal/mol, i.e., the "chemical accuracy".

Table 1: Energy comparison between full double an single precision implementations.

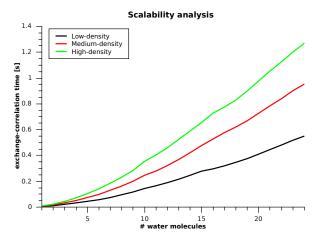
	Heme DZVP	Taxol 6-31G	Valinomycin 6-31G
CPU (H)	-2874.690057	-2923.013871	-3788.328471
GPU (H)	-2874.690164	-2923.014294	-3788.328135
$\Delta E(kcal/mol)$	0.07	0.26	0.21

3.3 Scalability Analysis

One important aspect to verify in the obtained implementation is the linear scalability (with the number of atoms) of the algorithm in practice. To this end, execution times for the exchange-correlation calculation were measured as explained previously for both the GPU and CPU implementations. This was done on systems consisting of a series of water clusters of growing size (1 – 24 molecules) with a DZVP basis-set and an auxiliary DGA1 basis-set. Three quadrature grids of different density were tested ^{22,26,27}: 50, 116 and 194 angular points, and 30 to 35 shells (depending on the element). The DFT-GGA functional PBE was used.

In Figure 7a we show, for the three grids available, the best times obtained for the GPU version.

It can be seen that linearity is reached for systems of five to six water molecules. For these tests we also show (Fig. 7b) the acceleration factor between the GPU and CPU implementations while performing these calculations.



(a) Scalability analysis: best times obtained for high density grids for the water clusters systems

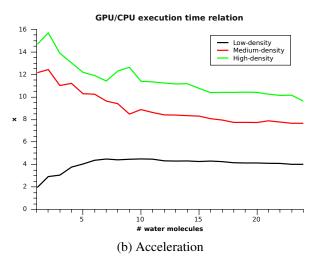


Figure 7: Scalability and acceleration analysis on the water cluster systems

3.4 Performance

3.4.1 Group partitioning

The use of a hybrid group partitioning scheme based on spheres surrounding the atoms and cubes for the rest of the points have a positive impact on performance. In Figure 8 we show the relative execution time vs. the percentage of the points grouped in the spheres, for the heme, taxol and Valinomycin.

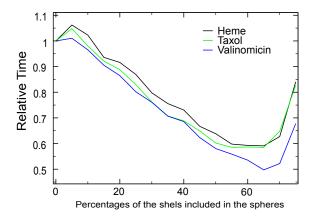


Figure 8: Relative time for the exchange and correlation terms, vs percentage of the points in the spherical groups.

In all cases the impact is similar, and the execution time is decreased by 40% without loss of accuracy, both in GPU and CPU implementation. The best results are obtained using a value between 50 and 70 % of the grid points for the spheres.

3.4.2 GPU vs **CPU**

In Table 2 we show a comparison of execution times for an iteration of the SCF calculation for the chosen molecules. It can immediately be seen that exchange-correlation calculations (and the corresponding Fock matrix elements) consumes the greatest part of the total time. It can also be observed that, although the CPU implementation isn't paralellized (which implies a potentially greater performance), there is a great reduction of the computation time by using GPUs, of more than then times in the computation of the exchange-correlation term, and close to twenty times in the Grid generation algorithm.

3.4.3 Comparison with existing implementations

Comparing a new implementation to other existing ones can be tricky. Although there are many electronic-structure implementations based on DFT, there is a great diversity of methods and approximations by which the desired result can be obtained. Thus, in this section we compare the performance of our implementation with others of

similar characteristics in order to ascertain if it measures up to the state of the art of the discipline.

In the first place, we perform calculations with the widely used ORCA software ²⁸, which implements highly efficient DFT algorithms, including the use of auxiliar basis for the ERIs calculation (but not memory allocation). Another valid comparison can be made against the TeraChem software, a quantum-mechanics implementation fully targeted for GPUs.

In Table 3 and Table 4 the times for grid generation and a single SCF iteration, respectively, are compared using the same three systems as in the previous sections¹. In all cases the same basis set and similar quadrature grids were used across implementations. However the calculation details may difer, for example Terachem recomputes the ERIs every iteration and does not use any auxiliar density.

Table 3: Comparison of iteration times (seconds) with other implementations.

	GPU	TeraChem	CPU	ORCA	ORCA
	(1x Fermi)	(8xC2050)	(serial)	(serial)	(4 cores)
Heme DZVP	4.29	-	34.28	42.56	13.4
Taxol 631G	3.70	2.00	30.3	58.7	20.7
Valinomycin 631G	6.40	3.24	38.6	107.0	35.14

Table 4: Comparison of grid initialization times (seconds) with other implementations.

	GPU (1 × Fermi)	ORCA (4 cores)
Heme	0.42	19.3
Taxol 6-31G	0.99	105.9
Valinomycin 6-31G	1.63	240.2

3.5 QM/MM simulations

The impact in the execution time on a QM/MM simulation was evaluated. Table 5 shows the execution time for a system composed of a quantum N-methylacetamide (NMA) in a periodic box of

¹Given that TeraChem doesn't inform clearly the grid generation times, this comparison is made against the ORCA software only.

Table 2: GPU/CPU performance comparison for selected systems

	Taxol			Valinomycin			Heme		
	GPU [s]	CPU [s]	CPU/GPU	GPU [s]	CPU [s]	CPU/GPU	GPU [s]	CPU [s]	CPU/GPU
Grid generation	0.99	19.33	19.53	1.63	30.78	18.88	0.501	11.95	23.85
SCF Iteration	3.70	30.3	8.19	6.40	38.6	6.03	4.29	34.28	7.991
Exchange-Correlation	2.41	28.83	11.96	3.5	35.33	10.09	3.38	33.55	9.93

550 TIP3P water molecules (tutorial included in a QM/MM of AMBER). The basis used in this case is DZVP and the entries show the overall time for 400 MD steps.

Table 5: Times per step in seconds in a QM/MM simulation of NMA in a box of 550 TIP3P water molecules

	GPU	CPU	acceleration times
SCF Energy	1.53	19.40	12.8
QM Force	0.57	3.56	6.2
QM/MM Force	0.64	0.67	1
Total simulation time per step	2.78	23.9	8.63

It can be seen that a significant acceleration is achieved due to the use of GPU. The Coulomb contribution (calculated in CPU) moderates the impact of the acceleration in the "QM force". The QM/MM force is calculated in CPU in all cases.

Finally in table Table 6 we show the times of a run of a heme protein, flavohemoglobin of E. Coli. In this case the QM system is composed of the heme moiety plus the distal histidine and the CO molecule (48 quantum atoms and 9 link atoms) with DZVP basis and approximately 40000 MM atoms (protein plus water). These times are averaged over 500 steps.

Table 6: Times per step in seconds in a QM/MM simulation of flavohemoglobin of E. Coli

	GPU
SCF Energy	141.3
QM Force	39.9
QM/MM Force	51.7
Total simulation time per step	235.9

4 Discussion

The aim of our work is to devise an electronicstructure calculation software based on DFT as efficient as possible, in order to be applied to hybrid molecular dynamic simulations. In this sense, the particularities of these type of calculations were considered. Of these, two are of great importance: the size of the systems (which usually consist of a moderate number of atoms, in the order of 100) and the nearness to convergence of the wave function at the first SCF iteration (which minimizes the number of iterations required). This second issue also means that the initialization time (grid generation, auxiliary density, etc.) has a greater relative weight with respect to single points calculations. The grid generation is almost 150 times faster than ORCA (see Table 4). In the SCF iteration part we can conclude that the use of an hybrid partitioning scheme reduces the computational cost by 40% and the use of GPU contributes in a 10X factor in the same sense. The comparison of the GPU code with TeraChem software also reveals the good performance of our implementation, since while the iteration time is less than twice slower, we employ only one GPU against the 8 GPUs server used in TeraChem performance measurements. An important clarification is that the iteration time involves others computation terms (such as Coulomb repulsion integrals) so the comparison is only partial. Another pertinent comparison can be made with Yasuda's implementation. In his work, the author obtains a total time for the density computation, gradient and corresponding Fock matrix elements of the Taxol, of 61.4 seconds. These same steps are performed in our implementation in 2.41 seconds, which would give a 25X speedup. Even when taking into account the less powerful graphical hardware used in Yasuda's analysis (GeForce 8800 GTX), it can still be concluded that our implementation seems more efficient. On the other hand, the QM/MM molecular dynamics present a very good performance even in the CPU code.

Taking these considerations into account and the results obtained we can conclude that we successfully developed an implementation of the exchange-correlation part of the DFT calculation that can measure up to the state of the art of the field, and also presents optimal characteristics to be included as part of a molecular dynamics simulation software.

On the other hand, the computational cost associated with the calculation of the interaction QM / MM and Coulomb forces are not negligible in the accelerated code. This raises the need to migrate these calculations to GPU.

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