Manipulating Visualization, Not Codes

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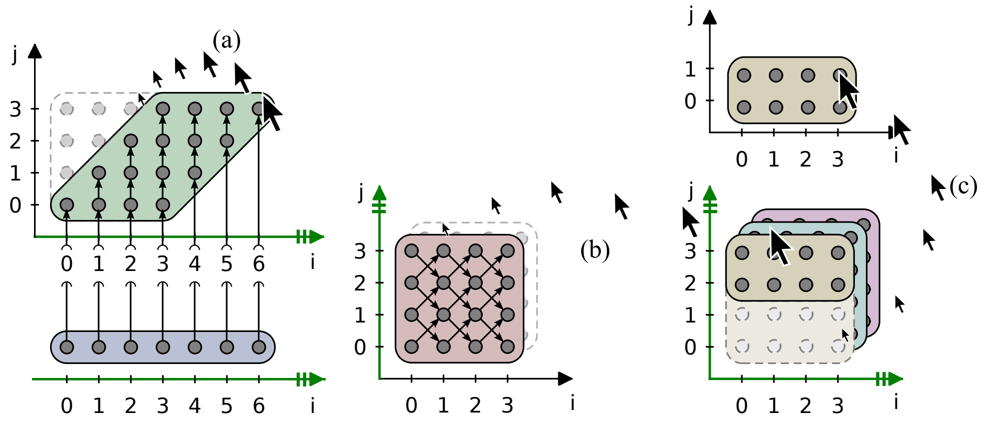

Figure 1: Directly Manipulating Visualized Polyhedra: (a) Skewing; (b) Reordering and Fusion; (c) Index-Set Splitting.

ABSTRACT

Manual program parallelization and optimization may be necessary to reach a decent portion of the target architecture's peak performance when automatic tools fail at choosing the best strategy. While a broad range of languages and libraries provide convenient ways to express parallelism, the difficult, time consuming and error-prone parallelism identification and extraction task is mostly left under the programmer's responsibility. To address this issue, we introduce a visualization-based approach to ease parallelism extraction and expression that leverages polyhedral compilation technologies. Our interactive tool, *Clint*, maps direct manipulation of the visual representation to polyhedral program transformations with real-time semantics preservation feedback. We conducted two user studies showing that Clint's visualization can be accurately understood by both experts and non-expert programmers, and that the parallelism can be extracted better from Clint's representation than from the source code in many cases.

1. INTRODUCTION

The massive adoption of modern and heterogeneous parallel architectures requires adequate solutions to support the creation and debugging of programs that efficiently exploit the full power of available parallel resources. Tremendous effort was made towards simplification of parallel programming by creating dedicated programming models, libraries or languages that express parallelism with high-level constructs. However, identifying parallelism remains a challenging task, especially when a deep data dependence analysis is required before parallelizing a sequential program.

The polyhedral model [8] has proven to be useful for loop-level parallelization or vectorization. Its unique instance-wise dependence analysis and transformation expressiveness makes it possible to apply aggresive program restructuring while preserving the original semantics. However, automatic polyhedral compiler techniques for loop-level parallelism extraction [5, 18] operate as heuristics-driven black-boxes that provide limited help and feedback to programmers when the computed transformation does not suit their needs. Semi-automatic tools based on directive scripts [6, 13, 9] offer more flexibility and control for program transformation, but they also require significant expertise from the end user. In this paper, we report on an interdisciplinary research project (Human-Computer Interaction and Optimizing Compilation) that aims to design and evaluate a new way to interact with a polyhedral framework through direct manipulation of visualizations.

Due to the geometric nature of its algebraic structures, the polyhedral model has a direct visual representation that is extensively used to describe program transformations in the literature. We have thus designed an interactive version of this visualization that allows to perform loop transformations, such as shifting, fusion or index-set splitting, through direct manipulation. This visualization is integrated into the interactive tool *Clint*[1] (Fig. 1) and features projections of the multidimensional loop nests containing individual iterations and dependences between them. *Clint* maps graphical manipulation of these objects to the corresponding polyhedral transformations and provides precise and direct feedback on semantics preservation during the manipulation.

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[1]Note: *Clint* will be demonstrated at the workshop. All visualizations in this paper are generated with *Clint*. A version of the tool with limited polyhedral backend was presented at the VL/HCC symposium in 2014.

Visualization is updated automatically whenever the source code is modified, while the transformed code may be generated on demand. Overall, our goal with *Clint* is not designing just an “interface” but consistent “interaction” between the programmer and the program restructuring engine [3].

In the following section, we present our visualization and the related interaction techniques. Section 3 details the support provided by the polyhedral framework to enable interactive manipulation. We report on the results of empirical evaluation of *Clint* in Section 4. Related work is discussed in Section 5, and conclusions are drawn in Section 6.

2. INTERACTIVE VISUAL FRONTEND

2.1 Design Rationale

Clint leverages the geometric nature of the polyhedral model by presenting statement instances and dependences in a scatterplot-like visualization. This approach is similar to the one commonly used in the polyhedral compilation community to illustrate iteration domains. However, it goes beyond these common static visualizations by allowing the direct manipulation [11] of the graphical objects in order to restructure the program. Each action performed by the user is mapped to a sequence of program transformations that, if applied, would change the original program structure so that its new visualization would corresponds to the one obtained after the direct manipulation. Furthermore, the set of possible interactive manipulations is based on the geometry-related vocabulary of classical loop transformations, such as skewing or shifting, providing the user with an intuition on the effect of the transformation.

The design of *Clint* is motivated by the needs for (1) a single and consistent interface for polyhedral program transformation and dependency analysis; (2) easier exploration of alternative loop transformations; and (3) reduced manual code and directive script editing. It relies on the polyhedral framework, but is not bound to any particular directive set or programming language as long as they may be expressed in the polyhedral model. It seamlessly combines loop transformations to allow for reasoning about execution order and dependences rather than loop structure and branch conditions. Finally, the interactive visual approach reduces parallelism extraction to visual pattern recognition [21] and code transformation to geometrical manipulations, giving non-expert programmers a way to manage the complexity of the underlying model [17].

2.2 Structure of the Visualization

One Statement Occurrence – The main structure of our visualization is a *polygon* that contains *points* on the integer lattice. Each point corresponds to an execution of a particular statement in the iteration of a loop nest, which is a statement instance in the polyhedral model. These points are linked by arrows to denote dependences between iterations. In Fig. 2(left), this polygon is displayed in the *coordinate system* where axes correspond to loop iteration variables. The polygon shape delimits loop iteration bounds.

Multiple Statement Occurrences – A transformation may result in a case where executions of a statement are distributed to multiple different loops. We then assume that this statement has multiple *occurrences*. *Clint* uses color coding scheme to match occurrences of the same statement both in the visualization and in the source code (see Fig. 3).

Multiple Coordinate Systems – Each coordinate system is at most two-dimensional and represents two nested loops. Statement occurrences that are enclosed in both loops are displayed in the same coordinate system but with optional slight displacement to discern them (see Fig. 3). Statement occurrences enclosed only in the outer loop share one axis of the coordinate system, forming a *pile* (see Fig. 1(left)). Finally, statement occurrences not sharing loops are displayed as a sequence of piles (see Fig. 1(right)). This structure represents the lexical ordering of the statement and loops in the source code and conveys their overall execution order.

Multiple Projections – The overall visualization is a set of two-dimensional projections, where loops that are not matched to the axes are ignored, and the program blocks containing statements are arranged according to their lexicographic order. For a single statement occurrence, they may be ordered in a scatterplot matrix as in Fig. 4. The points are displayed with different intensity of shade depending on how many multidimensional instances were projected on this point. We motivate this choice of two-dimensional projections by easier direct manipulation with a standard 2D input device (e.g. mouse) [3] as well as maintaining the consistency of the visualization for any dimensionality.

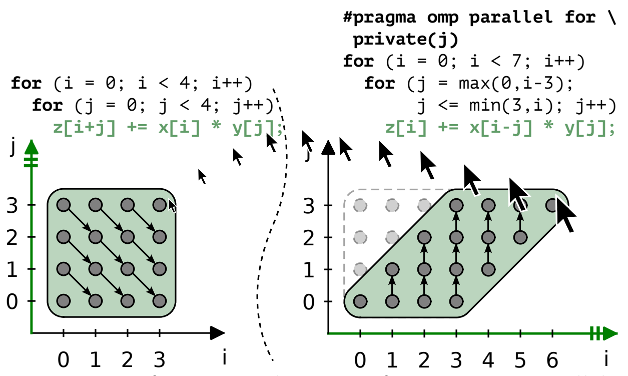

```
for (i = 0; i < 4; i++)
  for (j = 0; j < 4; j++)
    z[i+j] += x[i] * y[j];
```
```
#pragma omp parallel for \
 private(j)
for (i = 0; i < 7; i++)
  for (j = max(0,i-3);
       j <= min(3,i); j++)
    z[i] += x[i-j] * y[j];
```

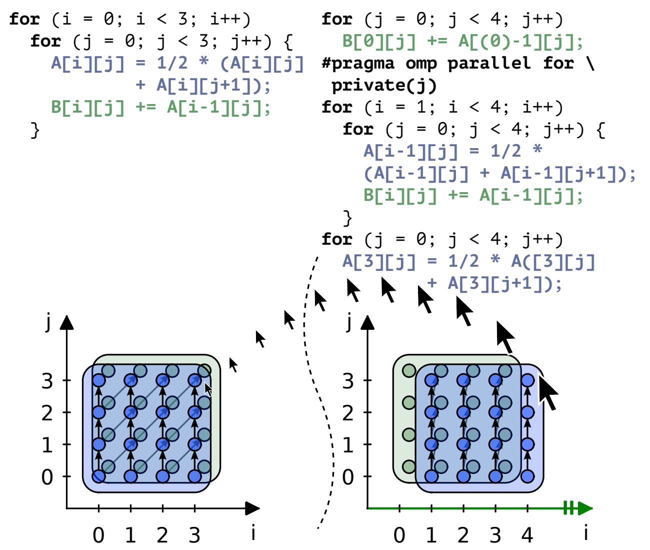
Figure 2: Performing a skew transformation to parallelize polynomial multiplication loop by deforming the polygon. The code is automatically transformed from its original form (left) to the skewed one (right).

2.3 Direct Manipulation to Restructure Loops

This visualization affords direct manipulation of its components. Depending on the strategy of restructuring to enable parallelism, points or groups of points can be dragged outside of their container polygon thus creating a new one (see Fig. 1(c)) in order to isolate irregular dependences or iteration groups that require strict execution order. Polygons can also be dragged within (Fig. 3) or between coordinate systems (Fig. 1(b,c)) to adjust the execution order between statements in the loop nest or move them to another loop nest. They can be reshaped so that the loop iterations are executed in a different order: for example, skewing prevents uniform dependences from spanning between iterations of the outer loop (see Fig. 2).

Coordinate systems within a pile or entire piles can be reordered by a dragging operation, as if they represented a list. This enables generalized reordering of statements and loops in the program and allows to analyze the overall data flow in order to find coarser-grain parallelism.

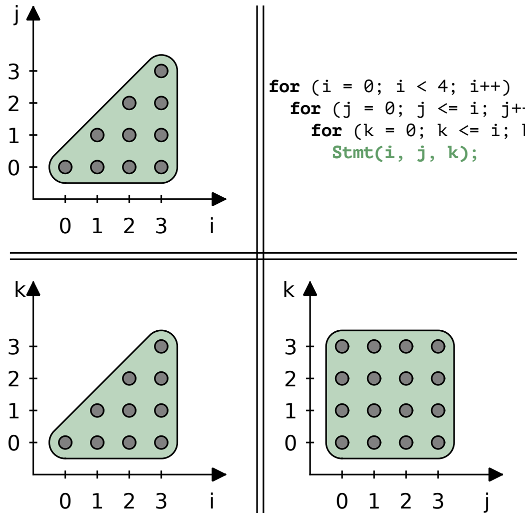
These manipulations can also be composed: for example, a group of points may be detached, dragged to another co-



```
for (i = 0; i < 3; i++)
  for (j = 0; j < 3; j++) {
    A[i][j] = 1/2 * (A[i][j]
            + A[i][j+1]);
    B[i][j] += A[i-1][j];
  }
```

```
for (j = 0; j < 4; j++)
  B[0][j] += A[(0)-1][j];
#pragma omp parallel for \
 private(j)
for (i = 1; i < 4; i++)
  for (j = 0; j < 4; j++) {
    A[i-1][j] = 1/2 *
    (A[i-1][j] + A[i-1][j+1]);
    B[i][j] += A[i-1][j];
  }
for (j = 0; j < 4; j++)
  A[3][j] = 1/2 * A([3][j]
          + A[3][j+1]);
```

Figure 3: Manipulation for *shift* Transformation: the darker polygon is dragged right so that dependence arrows become vertical without spanning between different iterations on `i`. On the right, the visualization is decoupled from the code structure, and both statements can still be manipulated as if they were not split between two loops.



```
for (i = 0; i < 4; i++)
  for (j = 0; j <= i; j++)
    for (k = 0; k <= i; k++)
      Stmt(i, j, k);
```

Figure 4: Multidimensional iteration domains are shown as two-dimensional projections in a scatter-plot matrix.

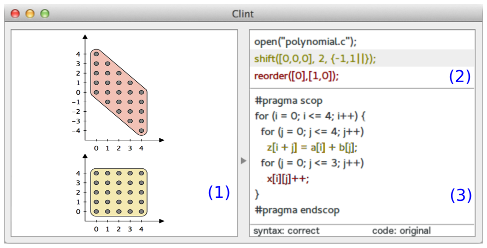
ordinate system and placed in a particular position during a single manipulation. After each action is performed, “legality” and “parallelism” feedback is provided: dependence arrows turn red and become thicker if the corresponding dependence is violated, and the axis becomes thicker and green if the corresponding loop may be executed in parallel (Fig. 3, right). This allows the user to resolve dependences by following visual intuition, e.g. by aligning all dependency arrows in parallel to each other, and thus to reveal parallelism without editing the source code or compiler directives.

In the case of a visualization with multiple projections, the selection of statement instance points has to be performed one by one in each projection, or by using a rubber band rectangle technique. The overall multidimensional selection is thus the intersection of constraints imposed by each separate two-dimensional selection. If there are no selected points in a projection, it is discarded, as it would result in an overall empty selection. *Clint* also handles parametric control flow conditions by providing identical visualizations and manipulation techniques for parameter values. It infers the parameters used in the selection and transformations and prefers parametric transformations in case of ambiguity.

In *Clint* we keep the visualization consistent with the original program structure unless the user explicitly applies the transformations to the code. This allows the manipulation of multiple disparate statement occurrences as a whole, for example in case of the partial loop fusion shown in Fig. 3.

Direct manipulation interfaces feature three promising capabilities for semi-automatic code restructuring. First, *selection of transformation target* – a particular iteration, group of iterations, statement or loop – is done directly on the graphical object, while in the code or polyhedral representation it may require additional identification methods relying on, e.g., lexicographic ordering of statements and inequations for iteration grouping. Second, *transformation composition* is as easy as sequencing graphical actions on the persistent visualization components with immediate feedback, even in cases where the underlying program structure evolves quickly. Finally, *transformation refinement* is possible thanks to editable transformation history view.

2.4 Clint Interface



```
open("polynomial.c");
shift([0,0,0], 2, {-1,1||});
reorder([0],[1,0]);
```

```
#pragma scop
for (i = 0; i <= 4; i++) {
  for (j = 0; j <= 4; j++)
    z[i + j] = a[i] + b[j];
  for (j = 0; j <= 3; j++)
    x[i][j]++;
}
#pragma endscop
```

syntax: correct   code: original

Figure 5: Clint interface includes: (1) interactive visualization, (2) editable history view, and (3) source code editor.

Clint combines three editable and synchronized representations: (1) the interactive visualization described above; (2) a navigable and editable transformation history view; and (3) the source code editor as shown in Fig. 5. A consistent color scheme is used between the views to match code statements to the visualization and to the history entries that affected these statements. User's manipulations are immediately appended to the history view using a special syntax to express high-level loop transformations [22]. The user can then navigate through the history by selecting an entry, which will update the visualization to the corresponding previous state. Entries may be edited as long as the syntax is respected (the system provides real-time feedback on syntax correctness and transformation legality). As the target code tends to become complex and unreadable after several manipulations, the user has the choice to update it or not in order to reflect the state of the visualization. Finally, when the code is edited, the visualization is updated, thus making *Clint* a dynamic visualizer for polyhedral code.

3. POLYHEDRAL BACKEND

The support for visualizing transformed instance sets and dependencies, for checking the legality of the complete transformation sequence, for marking axes as parallel and for ultimately generating the code that implements the transformation sequence is provided by a specific polyhedral framework. The overall architecture of Clint's framework is depicted in Fig. 6. Clint relies on well-known polyhedral compiler building blocks to achieve specific parts of the work. *Clan* [2] raises a C program to its polyhedral representation counterpart, *Candl* [2] achieves the data dependence analysis and the parallelism detection, and *CLooG* [1] generates a C+OpenMP code that implements a given transformation. A key aspect of these tools with respect to Clint's purpose is that they support the "*unions of relations*" polyhedral representation as recalled in Section 3.1. Clint also relies on two dedicated building blocks: *Clay* [2], which provides a high-level transformation formalism based on the unions of relations representation (Section 3.2); and a specific support to build the visualization and to translate user's actions to *Clay*'s formalism (Section 3.3).

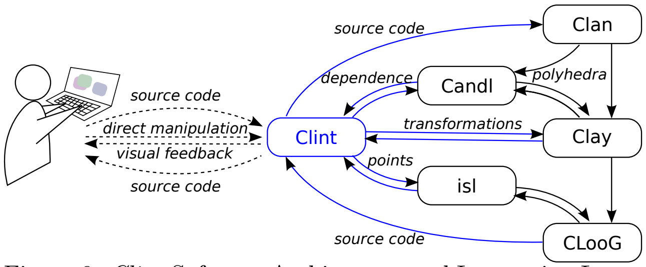


Figure 6: *Clint* Software Architecture and Interaction Loop: The user interacts only with *Clint* by entering the code and manipulating the visual representation. The system returns immediate feedback in the same interface and generates the transformed code on-demand.

3.1 Union of Relations Representation

Our work is based on a state-of-the art *union of relations* abstraction [12]. A union of relations is a piece-wise mapping from *input* dimensions to *output* dimensions according to affine constraints. We use this abstraction to represent all relevant components of an input program [2], and we consider only programs that can be abstracted in such a way. The relevant components include, for each statement, the statement's *iteration domain*, its *scheduling* and the list of its *memory accesses*.

The iteration domain of a statement captures the control structures surrounding it and abstracts all dynamic executions, or *instances*, of that statement. It is represented with a degenerate relation without input dimensions and where output dimensions correspond to the statement's iteration space. Disjunctions in control conditions result in the iteration domain being represented as a union of relations.

The scheduling of a statement expresses the ordering of its instances with respect to each other and with respect to instances of other statements. It is represented with a relation where input dimensions correspond to the original iteration space and where output dimensions correspond to the target multidimensional execution time. Each component of a union of scheduling relations may include constraints to limit the applicability of that scheduling component to specific parts of the original iteration space. A given iteration may have multiple mappings from multiple scheduling components (as a result, it will be duplicated in the final code).

A memory access relation abstracts accesses to a given variable or to indexed elements of a given array in a given statement. It is represented as a relation where input dimensions correspond to the original iteration space and output dimensions are the array dimensions. Approximations of memory accesses, e.g., when array indices are not affine expressions, may be represented as a union of relations.

3.2 High-Level Transformations

Supporting the direct manipulation of the polyhedral representation of a program requires a transformation mechanism with specific properties. First, it must be possible to precisely and independently select and transform any subset of a given iteration domain, or a complete iteration domain, or a group of iteration domains (*selection challenge*). Next, it must be possible to check at any moment the legality of the current state of the transformation and to allow illegal intermediate states while the user is designing the optimization (*composition challenge*). Finally, the user should be able to replay and to refine its optimization (*refinement challenge*).

Our solution to meet these requirements is a new high-level transformation formalism. Each user action is translated to a high-level directive which in turn modifies the scheduling relations. This new formalism, named after its implementation *Clay*, generalizes previous approaches that build high-level transformation directives on top of a polyhedral engine such as *UTF* [13], *URUK* [9] or *CHiLL* [6] by being based on the more general union of relations abstraction discussed in Section 3.1 and by strongly taking advantage of it. *Clay* and its dozen of directives corresponding to extended versions of classical loop transformations (reordering, shifting, interchange, fusion, splitting, index set splitting, strip-mining, grain, reversal, skewing, tiling etc.), are detailed by Bastoul in [2].

Clay addresses the selection challenge thanks to a specific structure of the scheduling relation, an extension to unions of relations of the so-called "2d+1" scheduling relation structure where odd dimensions are constant and represent the lexical order of statements at a given loop depth. The vector of such constants, named β-vector for consistency with URUK's formalism, is unique for each union of relations component and is guaranteed to remain unique by the formalism. Combined with the ability to apply index-set splitting as an additional scheduling relation constraint if a subset of a given iteration domain is involved, any selection corresponds to a set of β-vectors or β-vector prefixes and the desired transformation can be applied only to each scheduling component that has one of them.

The composition challenge is met because the formalism only modifies the scheduling relations, even for transformations that would require iteration domain alterations or duplications in previous approaches, such as *tiling* or *index-set splitting*. As a result, it is not necessary to apply intermediate dependence graph updates, as in URUK, or to enforce each step is legal, as in CHiLL, to ensure the legality of the complete transformation sequence. Because all iteration domains are immutable in *Clay*'s formalism, only the final scheduling has to be checked for dependence violations.

Finally, *Clay* meets the refinement challenge because the sequence of user actions translates to a list of directives: it is thus possible to undo, save, replay or refine. The user may keep the original code along with the transformation script made with *Clint* to achieve a clear decoupling between the program and its optimization.

3.3 Visualization Support

Scheduled Iteration Domains and Dependences – To convey information about the original or transformed execution order of statement instances, we use *scheduled iteration domain* visualizations. They are built separately for each scheduling relation component of each statement. First, we set parameters to (user-)defined constant values in order to generate a finite visualization. Next, we remove special β-vector dimensions (see Section 3.2). Then we apply the Generalized Change of Basis to the iteration domain with respect to the scheduling relation component to get a scheduled iteration domain part [14, 1]. Finally, we rely on *isl* [20] to enumerate points in this domain to be displayed. In the same way, we use *Candl* [2] to compute instance-wise data dependence sets restricted to displayed statement instances only and to expose them. We also perform a violated dependence analysis generalized to union of relations in order to highlight violated dependences [19, 2].

Coordinate Systems and Piles – Special β-vector dimensions are not considered for scheduled iteration domain visualizations but are used to organize them into polygon stacks and coordinate systems piles instead. Two scheduled iteration domain visualizations share their first n coordinates if the first n components of their β-vectors are the same. For a projection on the iteration space dimensions n and m where $n < m$, the visualizations are stacked in one coordinate system if they share m β-vector components, while coordinate systems are arranged in piles for visualizations sharing only n β-vector components.

Instance-Wise Selection – To operate on an arbitrary set of selected points, a polyhedron containing these points must be defined first. As an initial approximation, we compute a convex hull for these points and construct a set of all integer points within it. Then, we compute a set of difference between convex hull points and selected points. If it is empty, the convex hull is used, otherwise we check if the remaining points fit a multidimensional linear function. In this case, the function is used as a constraint with an existentially quantified dimension instead of the constant to complete the convex hull, otherwise we discard the transformation until the selection is updated. Although discarding several irregular selection cases, this algorithm offers reasonable trade-off between performance and typical case coverage.

4. EVALUATION OF CLINT

We conducted two controlled experiments to evaluate *Clint*'s design and assess its benefits over manual parallelization methods. In the first experiment, we focused on the visual representation and in the second we compared its direct manipulation approach with manual code transformation.

4.1 Exp. 1: Suitability of the Visualization

In this experiment, we assess the suitability of our visual representation of program statements in the polyhedral model. Although similar visualizations have been already used for descriptive or pedagogical purposes, there is no empirical evidence of their appropriateness for conveying program structures. In order to inform the design of *Clint*, we are testing whether programmers with different expertise in parallel programming and optimizing transformations are able to deduce the corresponding code from a visualization and vice versa, at several levels of difficulty.

Participants – We recruited 16 participants – 12 male, 4 female, aged 18-53 – from our organizations. All of them have experience in imperative programming with C-like languages and previous knowledge of the polyhedral model. Six participants already used iteration domain visualizations in their work and were thus considered as experts.

Procedure – The experiment is a [3 × 2] between-subject design with two factors:

- Task: (i) writing a code snippet which corresponds to the given visualization using a C-like programming language, which had loops and branches with affine conditions (*VC*); (ii) drawing an iteration domain visualization given the corresponding code (*CV*).
- Difficulty: problems may be (i) two-dimensional with constant bounds (*Simple*); (ii) multi-dimensional with constant bounds (*Medium*); (iii) two-dimensional with branches and mutually dependent bounds (*Hard*).

In order to avoid learning effect and to ensure consistent difficulty over tasks, participants were divided in two groups with the same number of experts. Group 1 was asked to perform the visualization to code task (*VC*), and group 2 the code to visualization task (*CV*). The order of task difficulty was counterbalanced across participants. Both tasks were performed on paper, with squared graph paper for the *CV* condition. Participants were presented with the visualization and did two practice tasks at the beginning of the session. They were instructed to perform the tasks as accurately as possible without time limit and were allowed to withdraw from a task. Expected solutions were shown at the end of the experiment. Each session lasted about 20 min.

Data Collection – For each trial, we measured Completion Time, Error and Abandon rates. The errors were split in two categories: *type I*, the shape of the resulting polyhedron was drawn correctly, but linear sizes or position were wrong; *type II*, the shape of the polyhedron was incorrect. Codes describing the same iteration domain were considered equivalent (e.g. `i <= 4` and `i < 5`). We also videotaped participants activity and collected the materials they produced. After they completed the study, participants were asked about their strategies to accomplish the task as well as any suggestion on the visualization.

4.1.1 Results

We did not observe any significant learning effect and we discarded the trials in which the participants produced syntactically incorrect or not static control code.

Completion Time – We found a statistically significant effect of Difficulty with all difficulty levels being different (*Easy* = 114.3s, *Medium* = 235.8s and *Hard* = 437.9s). We also found a significant Expert×Difficulty interaction, which is explained by better performance of experts for the *Hard* tasks (319s vs 556s, see Fig. 7).

Errors – Participants performed the tasks with very low error rates (*VC* = 8.3%, *CV* = 4.1%). We observed only two withdrawals during a trial, both from non-experts, and after a significant amount of time. For the type of errors, some non-experts were not able to propose code for some hard tasks, while experts mostly made type I errors for some medium tasks (Fig. 8). However, it is hard to conclude on the causes of errors with such low error rates.

Qualitative Data – Participants' feedback also allowed us to improve the visualization since some of them noticed that overlapping statements and visual axis sharing could be in-

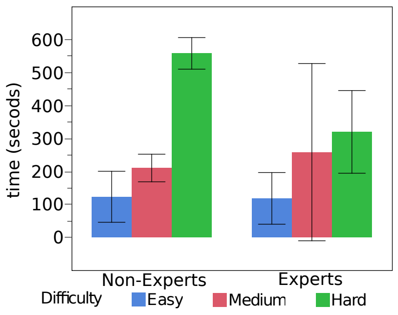


Figure 7: COMPLETION TIME increases with task difficulty but is lower for *experts*.(Error bars show 95% confidence intervals)

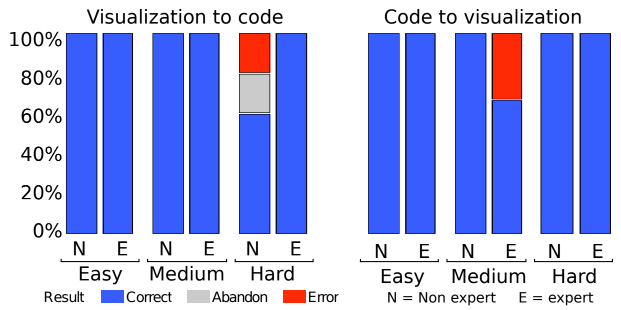


Figure 8: Percentage of errors and withdrawal: experts were slightly more successful than non-experts, but failed at simpler tasks. Only non-experts abandoned tasks. The overall error rate is less than 10% for each task.

terpreted ambiguously. Half of them also stated that the visualization significantly helps to understand the program structure, 31% that it rather helps and 19% that it does not change their level of understanding, but does not harm.

Overall, these results suggest that both experts and non-experts programmers were able to reliably map our visualization to the corresponding code, most of them stating that it has potential in assisting them in understanding programs. While the task they performed in this study does not belong to the program parallelization process, it shows that the scheduled iteration domain visualization is an efficient representation of static control parts of the program.

4.2 Exp. 2: Benefits of Direct Manipulation

In this second experiment, we compare *Clint* with common manual code transformation. Beyond the preliminary assessment of its efficiency, we are also interested in its acceptability by expert programmers who are more used to text-based interfaces. Participants who already took part in the first experiment were asked to perform some parallelization tasks at several levels of difficulty and in three conditions: source code (the baseline), *Clint* without source code, and *Clint*, the latter assessing participants' preference between direct manipulation and source code editing. Our hypotheses are that *Clint* can improve programmers accuracy and efficiency when parallelizing code, but also that the direct manipulation approach is likely to change their strategy when they address a parallelization problem.

Participants – Eight participants took part in this experiment (5 male, 3 female, aged 23-47). All of them had participated in the first experiment, and were thus familiar with the polyhedral model and our visualization.

Apparatus – The experiment was conducted with a specific version of our *Clint* prototype, implemented in C++, on a 15" MacBook Pro. Participants were interacting with a keyboard and a mouse. The language used was a subset of an imperative language with C-like syntax.

Procedure – The task consists in transforming a loop-based program so that the maximum number of loops becomes parallelizable, i. e. without any dependences that prevent parallel execution. Participants were asked to transform the program, but not to write the actual parallel code in order to avoid bias from individual expertise in using a particular parallel language. The experiment is a $[3 \times 3]$ within-subject design with two factors:

- TECHNIQUE: (i) code editing (*Code*); (ii) direct manipulation without code (*Viz*); (iii) full interface, with direct manipulation and source code editing (*Clint*).
- DIFFICULTY: (i) two-dimensional case with at most two transformations (*Simple*); (ii) two- or three-dimensional case with rectangular boundaries and at most three transformations (*Medium*); (iii) two- or three-dimensional case with non-trivial boundaries and at least two transformations (*Hard*).

Trials were grouped in three blocks by TECHNIQUE. The *Code* and *Viz* blocks were presented first in counterbalanced order across participants. *Clint* was always presented last, in order to assess participants' preference in using code editing or direct manipulation. In each block, participants were presented with one task of each difficulty level in random order (tasks were different from one block to another). The tasks were drawn from real-world program examples and simplified (see Appendix B). Trials were not limited in time and participants were asked to explicitly end the trial when they thought to be done, whether they succeed or not. Prior to the experiment, participants were instructed about source code transformations and the corresponding direct manipulation techniques. They also practiced 4 trials of medium difficulty for each technique and were allowed to perform two "recall" practice trials before each TECHNIQUE block. Each session lasted about 60 minutes and participants answered a short questionnaire at the end.

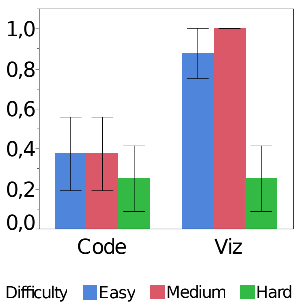
Data Collection – For each trial, we measured: (i) the overall trial COMPLETION TIME; and (ii) TRANSFORM TIME, the amount of time from the start to the first change in the program structure (code edited or visualization manipulated). We recorded both final and intermediate transformations to the program.

4.2.1 Results

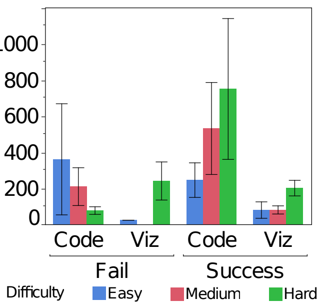
We did not observe any significant ordering effect of TECHNIQUE or DIFFICULTY on COMPLETION TIME and SUCCESS RATE. Because this experiment was conducted with a small sample, we opted not to conduct any statistical analysis.

Accuracy and Efficiency – Fig. 9a shows the SUCCESS RATE, defined as the percentage of trials where all possible loops became parallelizable, for each TECHNIQUE and in each DIFFICULTY condition. Despite large variability, it suggests that participants were in general more successful to find the expected transformations with direct manipulation than with code editing for *Easy* and *Medium* tasks (about 90% success rate vs 40%). For the *Hard* condition however, SUCCESS RATES are very similar (around 25%). Fig. 9b also suggests that participants often performed faster and that COMPLETION TIME is likely to be more consistent over participants with the direct manipulation interface (smaller standard error).

Strategy and exploration – In terms of strategy, the ra-



(a) Success Rate



(b) Completion Time (s)

Figure 9: (a) Success Rate is higher with *Clint* for *Easy* and *Medium* tasks, but similar to *Code* for *Hard* tasks. (b) Average Completion Time is often lower with the *Viz* technique, especially when tasks were successfully performed. (error bars show 1 standard error from the mean)

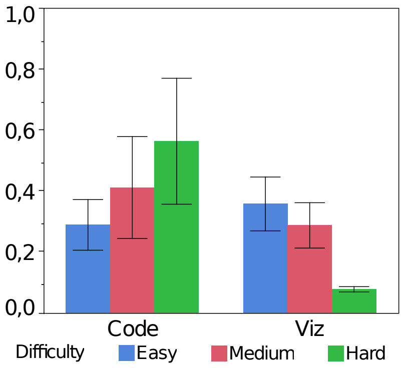


Figure 10: Ratio of first change time to completion time. The change in trend between different techniques can be caused by an improved problem understanding and favorisation of exploring different transformations. (error bars show 1 standard error from the mean)

tio of tasks were participants at least tried to perform a transformation is of 76% with *Code*, against 94% for *Viz*. Additionally, we observed that the time it took to participants to start modifying the program is of 135s on average with *Code* against 13s with direct manipulation. We also computed the ratio Transform Time/Completion Time as a measure of "engagement" of the participants (a lower value meaning that the participant started to transform the program faster). As shown in Fig. 10, this ratio increases with difficulty for *Code*, but drastically decreases for *Viz*. It suggests that participants were more likely to adopt an exploratory strategy for hard transformation problems with the interactive visualization than with code editing.

Code editing or direct manipulation? – For the *Clint* condition, we observed that all the participants used the interactive visualization and that only three of them edited the code during the first 30s of two trials on average before switching to the visual interface (12% of all the trials). In the post-experiment interview, these participants explained that they were trying out the code-visualization mapping or changing the code for the sake of analysis. We found Success Rate and Completion Time to be very similar to those with only the visualization. Qualitatively, we observed that several participants were examining the original and transformed source code, but not editing or selecting it. These results suggest that most users would prefer using the visual interface to perform transformations, but still need the source code view to have a link with conventional program editing approach.

4.3 Discussion

Although conducted with a small number of participants and on targeted tasks, this preliminary study gives interesting insights into the appropriateness of *Clint*'s direct manipulation approach for program parallelization. First, in terms of performance and accuracy, it suggests that the interactive approach could help programmers to accurately extract parallelism and apply transformations faster than with standard tools. However, we only compared *Clint* with manual code editing as a baseline, and we did not consider automatic/semi-automatic approaches (e.g. *Pluto* [5] or *Clay* [2]) that could also assist users in managing the complexity of parallelization tasks. We can expect *Clint* to be a good complementary approach anyway, since it builds upon these tools in order to give more control to the programmer.

We also observed that *Clint* effectively changed programmers strategy. It allows them to explore and manipulate programs structure from the very beginning of the task, thanks to its visual affordances and transformation undoability. Clint may also favor attention switch from syntactical constructs like loops to dependences in data flow. We believe that this "active" exploration approach could help programmers to better learn some typical solutions to given situations, to recognize those situations thanks to visual patterns, and to reuse the gathered knowledge in new situations [21]. This would however require deeper investigations and long-term field studies on the usage of *Clint*.

Our preliminary tests and studies of *Clint* revealed good acceptance by expert programmers, who are known to be reluctant to use visual programming tools. We believe that the way *Clint* allows direct manipulation of the concepts that programmers use for parallelization favors its acceptance: instead of hiding its underlying complex model, *Clint* "reveals" it and helps to manage its complexity [17].

5. RELATED WORK

Visual Representations for Polyhedral Model – Scatterplot-like projections of loop iteration domains are extensively used in the literature on the polyhedral model. Popular polyhedral libraries provide interface to generate visualizations, such as *VisualPolylib* component for PolyLib [16] and islplot[2] for isl [20]. *LooPo* [10] visualizes dependences in iteration domains before and after automatic parallelization while *3D iteration space visualizer* [24] allows to mark desired dimension parallel to start automatic transformation search. Tulipse [23] integrates visual dependency analysis into the Eclipse IDE. These tools allow to interact only with the visualization while *Clint* translates manipulations back to the polyhedral representation and ultimately transforms the code to match the visualization.

Semi-Automatic Polyhedral Program Transformations – A handful of polyhedral frameworks provide a semi-automatic approach to program restructuring based on directive scripts implementing classical loop transformations, *UTF* being arguably the first of them [13]. *URUK* enables the composition of a complex sequence of transforma-

[2]http://tobig.github.io/islplot/

tions decoupled from any syntactic form of the program [9]. *CHiLL* enforces legality of each transformation in a sequence by intermediate dependence checks [6]. *AlphaZ* allows to redistribute data in the memory [25]. We propose an alternative formalism, *Clay*, that builds on unions of relations to provide high composition capabilities. We rely on it to convert visual actions to mapping relations without having user to input the textual form of the transformation sequence.

6. CONCLUSION

Clint brings intuition in loop parallelization by visualizing iterations with real-time feedback on data dependences, and enables program restructuring through graphical actions. It addresses challenges of semi-automatic approaches to loop transformations such as transformation composition and refinement or target selection. The results of our preliminary studies provided empirical evidence that the visualization approach is efficient and reliable, and confirmed the benefits of direct manipulation for the efficient exploration of possibilities for program parallelization. We believe our approach to be a promising first step towards better parallelization tools that leverage the power of analytical models by giving more control and expressiveness to programmers.

Our studies also revealed several possible improvements to *Clint* as well as new research directions: (1) enrich the editor with smooth transition between the original and transformed code and the visualization using advanced animation techniques [7]; (2) use three-dimensional transforms to reveal hidden or overlapping points and dependences; (3) provide dynamic visual feedback on the transformation legality and interactive guidance through manipulation restrictions/enhancements (e.g. pseudo-haptic feedback [15] or semantic pointing [4]); (4) investigate scaling of this approach to represent data flow in programs and expose coarser-grain parallelism; and (5) investigate the use of interactive visualization for learning parallelization and the polyhedral model.

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