Highly-Optimizing and Multi-Target Compiler for Embedded System Models

C++ Compiler Toolchain for the Component and Connector Language EmbeddedMontiArc

http://www.se-rwth.de/materials/ema_compiler
https://doi.org/10.5281/zenodo.1314370

Evgeny Kusmenko, Bernhard Rumpe, Sascha Schneiders, and Michael von Wenckstern*
Software Engineering, RWTH Aachen University, Aachen Germany, vonwenckstern@se-rwth.de

ABSTRACT

Component and Connector (C&C) models, with their corresponding code generators, are widely used by large automotive manufacturers to develop new software functions for embedded systems interacting with their environment; C&C example applications are engine control, remote parking pilots, and traffic sign assistance. This paper presents a complete toolchain to design and compile C&C models to highly-optimized code running on multiple targets including x86/x64, ARM and WebAssembly. One of our contributions are algebraic and threading optimizations to increase execution speed for computationally expensive tasks. A further contribution is an extensive case study with over 50 experiments. This case study compares the runtime speed of the generated code using different compilers and mathematical libraries. These experiments showed that programs produced by our compiler are at least two times faster than the ones compiled by MATLAB/Simulink for machine learning applications such as image clustering for object detection. Additionally, our compiler toolchain provides a complete model-based testing framework and plug-in points for middleware integration. We make all materials including models and toolchains electronically available for inspection and further research.

CCS CONCEPTS

• **Computer systems organization → Embedded software**;

KEYWORDS

code generation, model-driven software engineering

ACM Reference Format:
Evgeny Kusmenko, Bernhard Rumpe, Sascha Schneiders, and Michael von Wenckstern*. 2018. Highly-Optimizing and Multi-Target Compiler for Embedded System Models: C++ Compiler Toolchain for the Component and Connector Language EmbeddedMontiArc. In *ACM/IEEE 21th International Conference on Model Driven Engineering Languages and Systems (MODELS '18), October 14–19, 2018, Copenhagen, Denmark*. ACM, New York, NY, USA, 11 pages. https://doi.org/10.1145/3239372.3239388

MODELS '18, October 14–19, 2018, Copenhagen, Denmark

ACM ISBN 978-1-4503-4949-9/18/10…$15.00
https://doi.org/10.1145/3239372.3239388

1 INTRODUCTION

In embedded and cyber-physical systems software and physical components are deeply intertwined and mostly interact with their environment [45]; examples in automotive industry include ESC[1], ABS[1], TCS/ASR[1], EPS[1], LKAS[1], ACC[1], PW[1], and AFL[1]. Large German automotive manufacturers develop embedded systems using Component and Connector (C&C) models [8, 48], which are later translated to C/C++ code and deployed on embedded devices often exhibiting custom processor architectures. In test-driven modeling [57], which is part of agile development processes [1], it is very important that developers and/or continuous integration systems can test changes quickly and automatically - long compilation and test execution times may hinder the overall development process as slow tests may kill the developer feedback loop [43].

Our first contribution is a compiler toolchain infrastructure, designed with respect to automotive software development needs, for the C&C modeling language *EmbeddedMontiArc* [27]. This powerful cross-platform compiler serves a series of targets including *x86/x64*, as well as *ARM* and *WebAssembly*; thereby enabling deployment and execution on a variety of devices ranging from micro-controllers to tablets and smartphones. This compiler infrastructure is also highly configurable and combines different frameworks such as *Octave* [13] or *Armadillo* [44] as well as various BLAS (Basic Linear Algebra Subprograms) backends such as *OpenBLAS* [55] and *Intel MKL* [25] under the hood. The toolchain is completed by a model-based testing framework, a web-based IDE, and middleware integration.

Our second contribution are algebraic and threading optimizations for C&C models that can be derived automatically. These optimizations allow simulations on computationally complex tasks such as local traffic system scenarios for convoys, data mining or image processing tasks on standard personal computers in a small amount of time.

Our third contribution is an evaluation on four applications to measure the runtime performance for the generated code which is produced by compiling C&C models (an image clustering provided by the *MathWorks* homepage on matrix modifier applications) with the presented infrastructure on an x64 architecture as native code, as well as running it in a web-browser on a normal PC, and a smartphone. Thereby, we compare the runtime performance of the generated code when using the *Octave*

[1] Electronic Stability Control, Anti-lock Braking System, Traction Control System/Anti Slip Regulation, Electronic Power Steering, Lane Keep Assist System, Adaptive Cruise Control, Power Windows, Adaptive Forward Lighting

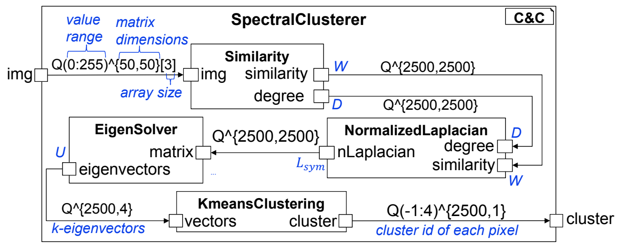


Figure 1: C&C architecture of the `SpectralClusterer`.

mathematics framework with the one when using the *Armadillo* library. During this case study we compare the runtime performance against the performance of code generated by *MATLAB/Simulink*, which is the de-facto C&C modeling framework in German automotive industry today, with equivalent models for native applications, and the runtime performance against *MathJS* code for web-browser applications.

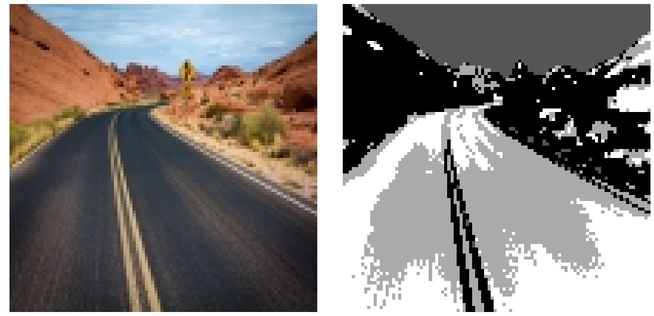
Finally, as an **important contribution of our work** we made our **entire toolchain** including its source code **and all models** needed for our comparison with other frameworks **public available** from http://www.se-rwth.de/materials/ema_compiler. Additionally we produced videos showing our complete setup and experiments, so that all results and experimentation steps are transparent to all readers. We encourage the reader to inspect these materials and use them for their own research.

The outline of this paper is the following: Section 2 presents the image clustering algorithm used as running example in paper. Section 3 shortly introduces the C&C modeling language *EmbeddedMontiArc*, tools needed for a multi target compiler platform such as *Emscripten*, *LLVM*, *clang* and *gcc*, as well as the two mathematics frameworks *Octave* and *Armadillo*. Section 4 contains our first contribution the complete compiler toolchain infrastructure. Section 5 presents our second contribution, the optimizations to speed up the runtime performance of the compiled code. Section 6 is the case study section comparing the runtime performance using different mathematics libraries, different BLAS backends, and running it on different targets as well as it compares run-time results when using *Simulink* or implementing the algorithms directly in *JavaScript* or in *Java*. Finally, Section 7 concludes this paper.

2 RUNNING EXAMPLE

We introduce two compelling running examples to thoroughly explore our approach of a highly optimizing multi-target compiler. The first one is an `ObjectDetector` employing spectral clustering for image recognition. The second one is a C&C model called `MatrixModifier` which performs different matrix calculations. In practice, these kinds of operations are pervasive in many domains including navigation and routing where maps are represented as large matrices and need to undergo various interpolations and transformations [20].

Object Detector. Unsupervised learning has proven to be an important tool-set for automated data understanding and pre-processing. One prominent application is image segmentation, e.g. enabling self-driving cars to separate objects in a scene captured



(a) (b)

Figure 2: Original image from Henning Witzel [54] (left) and the spectral clustering result (right).

by a camera. While there is no perfect clustering algorithm and the best fit is highly domain-dependent, *spectral* clustering methods are known to exhibit an outstanding performance in many complex applications [41, 49]. The basic idea is depicted as a C&C model in Figure 1 and can be summarized as followed. Let $x_{ij} \in [0, 255]^3$ be the 3-dimensional pixel value of an image at position (i, j) encoding a point in the HSV (hue, saturation, value) color space. For better handling, an $N \times M$ image is represented as a vector, mapping a position (i, j) to the vector index $M \cdot i + j$, where N and M are the height and the width of the image, respectively. First, a symmetric similarity matrix $W \in \mathbb{R}^{NM \times NM}$ is computed. Consequently, the entry of W at position (h, k) provides information on the similarity of the two pixels corresponding to the indexes h and k. Pixel similarity may be defined in terms of distance, color, gradients, etc. Second, the so called graph Laplacian is computed as $L = D - W$ where D is the so called degree matrix defined as $D = \mathrm{diag}\left(W \mathbb{1}_{N \times M}\right)$ with $\mathbb{1}_{NM}$ being an $N \cdot M$ dimensional column vector full of ones. Often it is advantageous to use the symmetric Laplacian

$$L_{sym} = D^{-\frac{1}{2}} L D^{-\frac{1}{2}} = \mathrm{diag}\left(\mathbb{1}_{\mathrm{NM}}\right) - D^{-\frac{1}{2}} W D^{-\frac{1}{2}} \qquad (1)$$

as outlined in [49]. For efficiency reasons, as they do not carry valuable cluster information the identity matrix and the minus depicted in red are often dropped in concrete implementations obtaining the simplified term highlighted in blue. Note that computing L_{sym} requires a matrix inversion on the diagonal matrix D as well as two matrix multiplications. Now the eigenvectors corresponding to the k smallest eigenvalues of L_{sym} have to be computed where k is the number of clusters we want to detect. If this number is unknown an index can be used to estimate it [12]. Furthermore, let U be an $NM \times k$ matrix with the k eigenvectors as its columns. Each row of this matrix represents one pixel in a feature space which should be easier to cluster by the standard k-means algorithm. Finally, the `ObjectDetector` can separate the objects shown in Figure 2 (a) as depicted in Figure 2 (b).

For our experiments we use the MATLAB implementation by Asad Ali [3], which is based on the original spectral clustering algorithm [49]. We extend the implementation by an image loader to allow images as input data.

The second example depicted in Figure 7 shows a component performing several common matrix modifications. To better grasp the performance benefits gained by using a smart code generator, this example is chosen to be rather abstract but quite computation intense when the code is written or generated in a naive way. Similar models are often utilized in computationally intense applications where a lot of information is stored and modified in matrices scattered over multiple components. Further details will be provided in the respective sections.

The full source of both examples modeled in *EmbeddedMontiArc* is available from [14].

3 PRELIMINARIES

C&C Modeling and EmbeddedMontiArc. The main aim of model-driven development is to model the domain knowledge, which in our case is the functionality of embedded systems. In contrast to a general purpose language programmer, the model driven developer should not care about performance issues like multi-threading or optimized algebraic routines. A good modeling language allows the expression of the domain knowledge intuitively and a smart compiler tool chain produces high-performance code to efficiently test and simulate the functional models.

EmbeddedMontiArc [27] is such a textual domain specific language to model logical functions in a C&C based manner. Especially, *EmbeddedMontiArc* places emphasis on the needs of the embedded, CPS (Cyber-Physical Systems), as well as the automotive domains and is particularly used for controller design [19]. As an example, the elaborate numeric type system allows declarations of variable ranges as well as accuracies. Furthermore, units are an inherent part of signal types and hence tedious and error-prone tasks like checking the physical compatibility of signals (weights cannot be added to lengths) as well as unit or prefix conversion (feet to meters, km to m) are delegated to the *EmbeddedMontiArc* compiler.

Figure 3 (a) - (c) show how the spectral cluster in Figure 1 is modeled in *EmbeddedMontiArc*. Figure 3 (b) and (c) represent the subcomponents of (a). As is inherent to C&C languages, the main language elements of *EmbeddedMontiArc* are `component` and `connect`. While the former defines a new component followed by its name, e.g. in line 1 of Figure 3 (a), the latter connects two ports of subcomponents with each other, e.g. in lines 10-15 in Figure 3 (a). The behavior of a component can be either defined by a hierarchical decomposition into subcomponents as in the case of Figure 3 (a) or using an embedded behavior description language.

The principal behavioral language used throughout this work is a matrix based math language, used in lines 6-8 and 5-14 of Figure 3 (b) and (c), respectively. As *EmbeddedMontiArc* is strongly typed, errors like wrong matrix dimensions are caught at compile-time, in contrast to *MATLAB/Simulink* where this is a runtime exception. A matrix property system leverages performance optimizations as well as further compatibility checks in the compilation phase. If a matrix is declared to be diagonal, both memory and computational complexity of the generated code can be reduced dramatically. If furthermore, the domain of the matrix is constrained to non-negative entries, it can be inferred that the matrix is positive-semidefinite allowing the inversion function to be used on it and guaranteeing that the result will be positive-semidefinite again [9].

As our spectral clustering example shows each *EmbeddedMontiArc* component resides in its own text file so that multiple users or teams can work on one large C&C modeling project simultaneously. Compared to other C&C languages where models are stored in a proprietary binary format in one single file, such as Simulink's slx format, this facilitates the usage of version control systems, merging, and conflict solving but also textual searching in model repositories.

The *EmbeddedMontiArc* language family has been developed using *MontiCore 5*, a language workbench particularly known for its leading language composition technology [22] and hence facilitating the integration of the main C&C architecture description language with behavior description, configuration, testing, and other sub-languages. However, *EmbeddedMontiArc* is not just a modeling language frontend but rather a holistic model driven software engineering methodology in the sense that all executable code and binary files are generated directly from *EmbeddedMontiArc* models, i.e., the developer does not have to deal with any target languages, compilation, and linking issues. Therefore, the heart of the proposed tool chain is an extensible highly-optimizing cross-platform compiler presented in the following sections.

Finally, the question arises how components developed in *EmbeddedMontiArc* can be tested and quality assured in continuous integration environments. Writing unit tests for the generated code using a framework of the target platform not only goes against our holistic model driven engineering principles, forcing the developer to understand the target details and to produce platform-dependent code but is also infeasible in the long run as the interfaces of the generated code might change. Instead we propose a so called *stream* language allowing a test developer to write black-box tests for *EmbeddedMontiArc* components by providing sequences of values for the input ports (test data) and the corresponding expected output.

In Figure 4 a *stream* test example is given for the `NormalizedLaplacian` component of Figure 3 (b) with the generic parameter `n=3`. In lines 3 and 4 we provide the test inputs for the ports `degree` and `similarity` whereas lines 5-8 specify the expected output of the port `nLaplacian`. The `tick` keyword separates the values of an input *sequence* allowing one to test the component behavior for arbitrarily long input and output streams. This is particularly important for stateful components such as PID controllers or automata. By specifying tolerance ranges using the $+/-$ operator as in lines 5-7 we can easily cope with floating point outputs, rounding errors, and numerical inaccuracies.

Multi Target Compiler Platforms. *Emscripten* [56], developed by Alon Zakai and Mozilla, is a *Low Level Virtual Machine* (*LLVM*) to *JavaScript* or *WebAssembly* (*WASM*) compiler.

LLVM is a modular and reusable compiler framework for arbitrary programming languages. The *LLVM* framework [28] enables transformations at link-, install-, run-, and idle-time, to optimize memory usage, runtime speed, and program size.

CLang is a *C*, *C++*, *Objective C/C++*, *OpenCL C* to *X86-32*, *X86-64*, and *ARM* compiler based on the *LLVM* framework. *CLang* is compatible with *GCC*, but uses less memory and compiles faster while still delivering programs with a better performance. On the other hand, *GCC* addresses more targets such as *PowerPC* or embedded processors. It supports any target architectures where `int` is 8, 16, 32 or 64-bit wide. A new target platform can easily be added by providing a machine description containing an algebraic formula for each available instruction [47].

```
EMA
component SpectralClusterer
   <N1 n=50, N1 k=4, N1 maxCls=1> {
 ports in Q^{n, n} img[3],
      out Q^{n, maxCls} cluster;
 instance Similarity<n> sim;
 instance NormalizedLaplacian<n*n> nL;
 instance EigenSolver<n*n,k> eS;
 instance KMeansClustering
   <n*n, k, maxCls> kMC;
 connect img[:] -> sim.img[:];
 connect sim.degree -> nL.degree;
 connect sim.similarity -> nL. similarity;
 connect nL.nLaplacian -> eS.matrix;
 connect  eS.eigenVectors -> kMC.vectors;
 connect kMC.cluster -> cluster;}}
```

(a) EmbeddedMontiArc model of `SpectralClusterer`.

```
EMA
component NormalizedLaplacian
                   <N1 n=2500> {
  ports in diag Q^{n,n} degree,
            Q^{n, n} similarity,
       out Q^{n,n} nLaplacian;
 implementation Math{
 nLaplacian=degree^-.5*
 similarity*degree^-.5;}}
```

(b) EmbeddedMontiArc model of atomic component `NormalizedLaplacian`.

```
EMA
 1 component KMeansClustering
 2   <N1 n, N1 nbVecs, N1 maxCls> {
 3  ports in Q^{n, nbVecs} vectors,
 4       out Q^{n, maxCls} clusters;
 5  implementation Math{
 6   Q^{n, nbVecs} UMatrix;
 7   for i=1:size(vectors,1)
 8     Q^{1, nbVecs} target =
 9                vectors(i,:) .^ 2;
10     Q amount = sqrt(sum(target));
11     UMatrix(i,:) =
12           vectors(i,:) ./ amount;
13   end
14   clusters=kmeans(UMatrix,maxCls);}}
```

(c) EmbeddedMontiArc model of atomic component `KMeansClustering`.

Figure 3: *EmbeddedMontiArc* code of selected components for the spectral clusterer model

```
                                                        Stream
stream LaplacianTest
  for NormalizedLaplacian<3>{
     Values for input ports
  degree:     [1, 0, 0; 0, 2, 0; 0, 0, 2] tick …;
  similarity: [0, 1, 0; 1, 0, 1; 0, 1, 1] tick …;
                         3 × 3 matrix
  nLaplacian: [0   +/- 0.05, 0.5  +/- 0.1,  0    +/- 0.05;
               0.5 +/- 0.1,  0    +/- 0.05, 0.25 +/- 0.1;
               0   +/- 0.05, 0.25 +/- 0.1,  0.25 +/- 0,1]
       tick …;
}                   Expected Values for output port
```

Figure 4: Stream test model of the `NormalizedLaplacian` component.

WebAssembly [51] is a size- and load-time-efficient binary instruction format for a stack-based virtual machine, and it aims to execute at native speed. *WebAssembly* runs on nearly all smartphone and desktop browsers [39], as well as on the nodejs server.

A generator toolchain supporting *GCC*, *CLang*, and *Emscripten* can run its code on multiple targets at the best possible performance. These targets include **many embedded platforms**, e.g. microcontrollers used in drones, **web-browsers** on computers, smart phones, or tablets as well as **native *x86/x64* applications** using optimizations such as threading and *SIMD* (Single Instruction Multiple Data) instruction sets, e.g. *SSE*, *MMX* and *AVX*, but also native *GPU* (Graphical Processing Unit) support for *CUDA* and *OpenCL*.

Octave and Armadillo. As explained above, the behavior of an *EmbeddedMontiArc* component can be implemented using a math language. For basic mathematical operations the so called Basic Linear Algebra Subprograms (BLAS) specification defines a set of low level routines such as matrix additions and multiplications. Examples of available BLAS implementations include the *Intel Math Kernel Library* [53] as well as *OpenBLAS* [55]. To get the last ounce of performance out of the executing processor, these BLAS libraries rely on hardware specific optimizations such as *SIMD* parallelization and multi-threading.

To generate component behavior code from the math model in the component implementation, e.g. in lines 4-11 of Figure 3 (c) the *EmbeddedMontiArc* compiler does not use BLAS libraries directly. Instead it lets the user choose between an *Octave* [13] or an *Armadillo* [44] backend. These two high level linear algebra and scientific computing libraries cover an even broader range of mathematical functions than the BLAS specification including matrix operations such as eigenvalue decomposition and k-means clustering while offering an easier to use interface. Internally, both *Armadillo* and *Octave* use an exchangeable BLAS backend to deliver the best possible performance.

4 TOOLCHAIN

EmbeddedMontiArc Production and Test Compiler. In Figure 5 we show a comprehensive overview of our *EmbeddedMontiArc* compiler infrastructure featuring its most important parts. This infrastructure consists of two parts: (1) The (production) compiler, depicted on the left side, translates textual *EmbeddedMontiArc* models to native code for different targets. (2) The test compiler, shown on the right side, translates textual *stream* test models to native programs executing the compiled native code of (1) and producing test result reports. One contribution of this paper is this toolchain generating native code for different targets as well as testing the generated native code.

The compiler behavior can be controlled via the command line interface (CLI), e.g. to specify the target platform. (1) In a first step the compiler invokes the *EmbeddedMontiArc-to-C++ Code generator*. The concrete output depends on the mathematics library chosen via CLI, since the C++ code for matrix creation using the Octave library differs significantly from the matrix creation code using the Armadillo library. (2) The generated C++ code is compiled and linked in a next step. Thereby our toolchain chooses the appropriate C++ compiler for the specified target and math library automatically. This hides technical details about compiler options and linker paths for including the required mathematics runtime library from the user. For example, *Octave* for *Windows 64-bit* is compiled with *GCC*, while *clang* is used for *Armadillo* on *Mac OS X*.

To benefit from the highly optimized BLAS libraries working only on primitive *Integer* and *Float* types, the compiler throws all units away and converts all variables and constant values during the C++ generation process to the corresponding SI base units.

If the *EmbeddedMontiArc* compiler needs to compile for the web browser target, the C++ code generator does not generate optimal source code as *WebAssembly* does not support C++ threads yet [6]. Also the linking process for *WebAssembly* is different as it cannot link other *WebAssembly* files at runtime yet [52]. For this reason, no runtime dynamic linking is supported and all libraries are linked

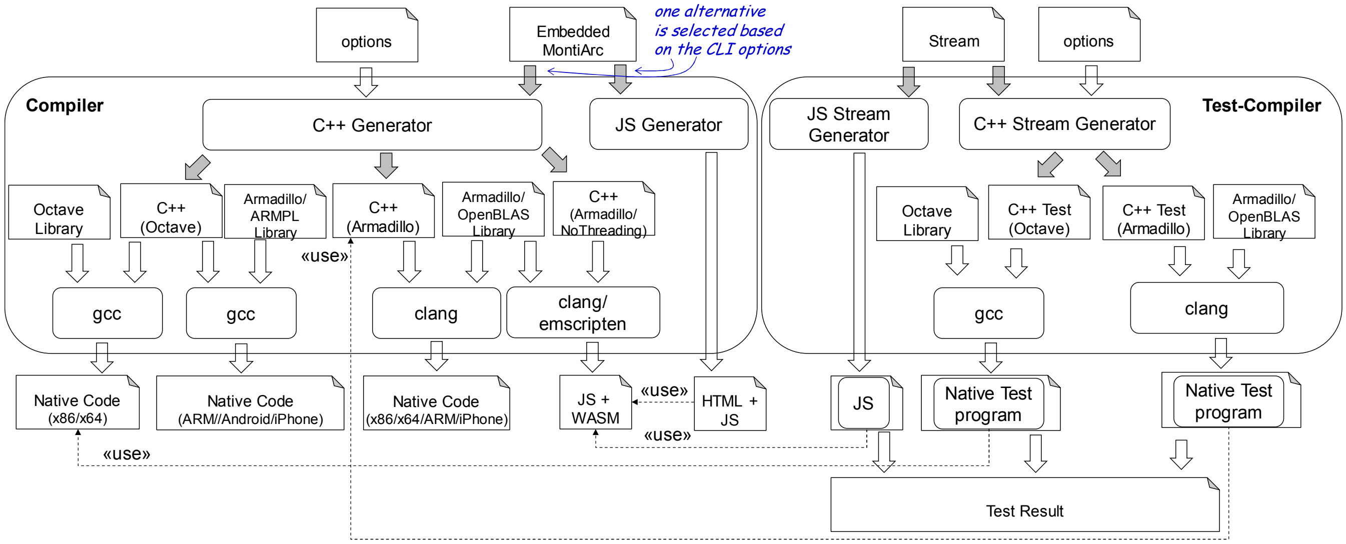


Figure 5: Compiler Infrastructure for *EmbeddedMontiArc* modeling family.

```
tags RosTags{   tagged symbol      tag type
tag nL.degree with RosConnection =
                    tag value
  {topic= (name=/deg, type=struct_msgs/Mat3)};
        RosConnection with provided middleware meta data
tag nL.W with RosConnection =
  {topic= (name=/w, type=struct_msgs/Mat3)};
      RosConnection with meta data generated from EMAM model)
tag nL.nLaplacian with RosConnection;
```

Figure 6: Tagging example for the `NormalizedLaplacian` component.

at compile time. Otherwise the communication would need to be based on JavaScript which would have a massive negative impact on the runtime performance.

Our compiler also configures *emscripten* locally, runs *clang* to compile the generated C++ code to *LLVM* and then runs *emscripten* to compile the *LLVM* code to *WebAssembly* and *JavaScript*. The options `NO_FILESYSTEM=1` and `O3` are used to produce smallest possible *JavaScript* files.

For the web-browser target we also generate an adapter allowing us to use the C&C model directly in *JavaScript*; the adapter also accepts matrices as Strings having the same convenient syntax as the matrices defined in *EmbeddedMontiArc* models. Since *JavaScript* is typeless, the generated *JavaScript* adapter also checks whether the input value fits to the type: are the matrix properties and the physical quantities compatible and is the value in the defined range. Additionally, the *JavaScript* generator produces an *HTML* file using the *JavaScript* adapter. Opening such an HTML file in a browser allows the modeler to test the component behavior by specifying input values by hand and receiving the calculated output values; examples of such generated HTML files are available from [14]. For the native code there are plug-ins allowing the developer to generate adapters for different middlewares.

Middleware Plugins. Since *EmbeddedMontiArc* was designed with a particular focus on embedded and cyber-physical systems, quickly the question arose, how models can be integrated into a vast amount of hardware and software platforms without having to vitiate them by technical details or to add hand-crafted glue-code. In domains like automotive, robotics, and cyber-physical systems both hardware and software architectures can be highly distributed. Thus, these systems often rely on middleware protocols such as *ROS* (*Robot Operating System*) to ensure loose coupling, exchangeability, and maintainability of the involved components.

Other C&C languages like *Simulink* [36] or *LabView* [24] enable the design of middleware-connected systems by providing corresponding component libraries. For instance, instead of outputting a computed actuator value to a standard output port of the system, the signal is sent to a pre-configured *ROS* [42] component which in turn handles the distribution of the message to a *ROS* network. Although easy to model and to use, the approach has serious drawbacks:

First of all, the algorithmic part of the system, e.g., the design of our clustering component, gets mingled with technical aspects of the system, thereby violating the separation of concerns principle and making the model platform-dependent.

Second, a variant of the model needs to be developed and stored for each target system or robot configuration. This inflates the required variant management overhead, although the actual model logic remains unaltered.

Third, models contaminated by middleware components exhibiting side-effects or having a behavior not only dependent on their inputs are difficult to test.

To avoid these pitfalls in model-driven engineering of embedded systems it is crucial to separate the conceptual model from the integration aspects. In *EmbeddedMontiArc* we achieve this aim by employing a so called *tagging language* to enrich the model by middleware specific information. Tagging allows adding information to the elements of a model such as ports in a separate *tag model* artifact [31]. Hence, the original model remains untouched and free of middleware specific information while all the information concerning the middleware interface of the system is gathered into a dedicated model.

If the original C&C model needs to be deployed in another ecosystem, the only thing the designer has to do is to write a new middleware tag model specifying which middleware has to be used and how ports and types are mapped to concepts of the middleware of choice. Middleware tags create middleware symbols in the symbol management infrastructure [37] of the *EmbeddedMontiArc* model. The original *EmbeddedMontiArc* code generator is unaware of these symbols and is hence not affected by the add-on. Instead, we provide a generator for each supported middleware.

The original C++ generator as well as the required middleware generators are registered with a supervisor orchestrating the generation process. Each generator creates code for the model parts, i.e. symbols, it can deal with. Finally, the orchestrating generator produces glue code melting the actual behavior code with the middleware adapters; thereby it produces an implementation ready to integrate into a simulator or on a real hardware system with zero hand-crafted code.

A tagging example for the `NormalizedLaplacian` component of Figure 3 (b) is given in Figure 6. We use *ROS* tags here to integrate the component into a *ROS* infrastructure. For the two input ports we provide full middleware meta data, i.e., a *ROS* topic name as well as the corresponding *ROS* type. It is important to provide this information if the model is integrated into a system with a predefined middleware infrastructure such as a simulator. If, however, the components to integrate are all designed in *EmbeddedMontiArc*, middleware meta data can be omitted and is generated by the corresponding middleware co-generator. Examples are: (1) *EmbeddedMontiArc* model controlling a *Gazebo* robot via *ROS* using the tagging system [11]; (2) *EmbeddedMontiArc* model controlling a *Torcs* car using *OpenDaVinci* [7] middleware [29]; (3) local traffic system with 10 cars [23] driven by an *EmbeddedMontiArc* controller in the MontiSim [16] simulator; and (4) an integration of the compiled `WebAssembly` code into the *JavaScript PacMan* simulator [18].

Further explanation videos describing the concrete models and the *EmbeddedMontiArc* development environment using this compiler toolchain are available under Youtube [38, 50].

5 OPTIMIZATIONS

This section presents our second contribution: algebraic and threading optimizations of the C++ code generator. Algebraic optimizations are particularly important for data intensive mathematical matrix-based tasks such as image processing or discretizing ordinary or partial differential equations [4] modeling control systems. Threading optimizations distribute all calculations defined in components into different threads. The effect depends mainly on the target CPU architecture, especially the number of available cores.

Algebraic Optimizations. All algebraic optimizations are explained with our running examples, namely the the`SpectralClusterer` and `MatrixModifier` model.

Following the definition in (1), the `NormalizedLaplacian` component of the `SpectralClusterer` shown in Figure 3 (b) needs to calculate the inverse square root of the degree twice. Note that we use the simplified definition highlighted in blue in order to be comparable to the publicly available *MATLAB* implementation also using this variant. Since the degree matrix is a diagonal matrix having non-zero entries only on its main diagonal the inverse square root of degree is just the element-wise inverse square root of all elements of the principal diagonal, i.e.,

$$\text{D is diagonal matrix}: \left(\mathrm{D}^{-0.5}\right)\Big|_{(i,j)} = \begin{cases} 0 & \text{for } i \neq j \\ \left(D|_{(i,i)}\right)^{-0.5} & \text{else} \end{cases} . \quad (2)$$

The type system of *EmbeddedMontiArc* is based on the mathematical domain allowing one to declare a matrix to be diagonal, tridiagonal, symmetric, positive-definite, etc. The C++ generator uses these matrix types to select the best suited algorithms [30] for inverting matrices. In most cases (not in the case of diagonal matrices though) when a matrix inversion is combined with a vector or matrix multiplication, e.g. $A^{-1}x$, no explicit matrix inversion is calculated. Instead linear equation solving algorithms are applied.

Other common compiler optimizations like caching computational expensive results to avoid recomputing the same problem are also implemented; for instance, the two occurrences of degree$^{-0.5}$ in lines 7-8 of Figure 3 (b) are replaced automatically by a helper variable. At compile-time, the type inference mechanism of *EmbeddedMontiArc* allows one to derive not only the matrix dimensions but also the algebraic type. Thus the compiler knows that degree$^{-0.5}$ is a diagonal matrix, as well, and is hence able to choose the best suitable multiplication algorithm only considering the principal diagonal for the left side expression in degree$^{-0.5} \cdot$ W. The aforementioned statical algebra analyses together with the presented optimizations improve the efficiency of the generated code dramatically.

The next paragraphs show algebraic optimizations based on the matrix dimensions [21] to figure out the best execution order to evaluate matrix expressions. Equations (3) – (6) summarize the formulas used for optimizations, where A, B, and C are matrices, b is a vector, and λ is a scalar:

$$\mathrm{AC} + \mathrm{BC} = (\mathrm{A} + \mathrm{B})\mathrm{C} \quad (3)$$

$$\mathrm{CA} + \mathrm{CB} = \mathrm{C}(\mathrm{A} + \mathrm{B}) \quad (4)$$

$$\mathrm{A}(\mathrm{BC}) = (\mathrm{AB})\mathrm{C} \quad (5)$$

$$\mathrm{A}(\mathrm{B} \cdot \lambda) = (\mathrm{AB}) \cdot \lambda. \quad (6)$$

Since the matrix optimizations of equations (3) and (4) are independent of the matrix type and, thus, can be applied always, tools such as *Armadillo* rewrite expressions following these two rules by using C++ function templates. The `MatrixModifier` component example, shown in Figure 7, illustrates the optimization process using equation (5); (6) is a special case of (5) with λ being a scalar. `MatrixModifier` consists of five input ports, one output port, and four `Multiplication` subcomponents. Based on the matrix dimensions defined in the ports and the mathematical expressions you can estimate the number of needed operations for each atomic component; e.g. multiplying a 5×7 matrix with a 7×10 matrix needs $2 \cdot 5 \cdot 7 \cdot 10 = 700$ arithmetic operations.

Equation (7) shows the natively derived calculation of the `MatrixModifier` component based on its C&C structure and the the estimated operations (est. ops) needed for all calculations; for the sake of clarity all matrix dimensions of the input ports and of the intermediate results are shown, as well. The estimated total number of operations needed to perform all the calculations of the `MatrixModifier` component is the sum of all estimated (single) operations, in our case $4\ million + 40\ million + 20\ million + 200\ billion \approx 220\ billion$ estimated operations.

$$\underbrace{\overbrace{\left(\underbrace{\overbrace{\left(\underbrace{\overbrace{\left(\underbrace{\text{mat1}}_{1\,000\times2}\cdot\underbrace{\text{mat2}}_{2\times1\,000}\right)}^{4\,000\,000\text{ est. ops}}}_{1\,000\times1\,000}\cdot\underbrace{\overbrace{\left(\underbrace{\text{mat3}}_{1\,000\times2}\cdot\underbrace{\text{mat4}}_{2\times10\,000}\right)}^{40\,000\,000\text{ est. ops}}}_{1\,000\times10\,000}\right)}^{20\,000\,000\,000\text{ est. ops}}}_{1\,000\times10\,000}\cdot\underbrace{\text{mat5}}_{10\,000\times10\,000}\right)}^{200\,000\,000\,000\text{ est. ops}}}_{1\,000\times10\,000} \tag{7}$$

$$\underbrace{\overbrace{\underbrace{\overbrace{\left(\underbrace{\text{mat1}}_{1\,000\times2}\cdot\underbrace{\overbrace{\left(\underbrace{\text{mat2}}_{2\times1\,000}\cdot\underbrace{\text{mat3}}_{1\,000\times2}\right)}^{8\,000\text{ est. ops}}}_{2\times2}\right)}^{8\,000\text{ est. ops}}}_{1\,000\times2}\cdot\underbrace{\overbrace{\left(\underbrace{\text{mat4}}_{2\times10\,000}\cdot\underbrace{\text{mat5}}_{10\,000\times10\,000}\right)}^{400\,000\,000\text{ est. ops}}}_{2\times10\,000}}^{40\,000\,000\text{ est. ops}}}_{1\,000\times10\,000} \tag{8}$$

If the estimated operation count surpasses a specified threshold, the compiler starts to restructure the expressions. To deliver a reasonable trade-off between compilation and runtime performance, the compiler only optimizes computationally expensive expressions. Applying rule (5) transforms equation (7) to equation (8). However evaluating (8) needs only $8\ thousand + 8\ thousand + 400\ million + 40\ million \approx 440\ million$ estimated algebraic operations. Compared to the originally needed 220 *billion* operations, our algebraic optimization reduces the calculation effort by a factor of 500. This factor holds only for algebraic computations, but a program must also load the matrices from the RAM to the processor caches and store them back into the RAM again since these large matrices need several hundreds of megabytes of storage and do not fit into the L3 cache. The case study in the next section shows that the real runtime benefit achieved by rewriting the mathematical formula is only a factor of 8. But real-world image processing systems consist of large hierarchies of filter components offering much more optimization potential then our small `MatrixModifier` example with only four matrix-processing subcomponents.

Threading Optimizations. The threading analysis tries to detect independent calculation paths to schedule them on different CPU cores. All threading optimizations are executed after doing the previously mentioned algebraic optimizations. Since our toolchain presented in Section 4 uses different BLAS backends such as *OpenBLAS*, some parallelizations on matrix operations can already be done by these libraries.

Thus, the C++ generator has to find a trade-off regarding the number of threads created by itself and the BLAS backend, respectively.

In general it should be avoided to create more threads than the target architecture supports physically (number of cores plus hyper-threading[26]) as this results in scheduling overhead for the operating system and reduces the overall performance.

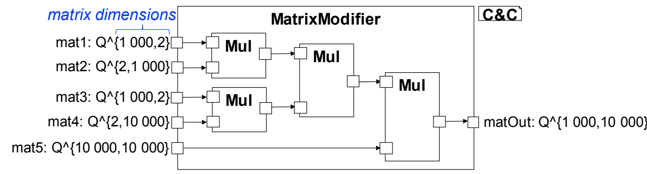


Figure 7: C&C architecture of `MatrixModifier`.

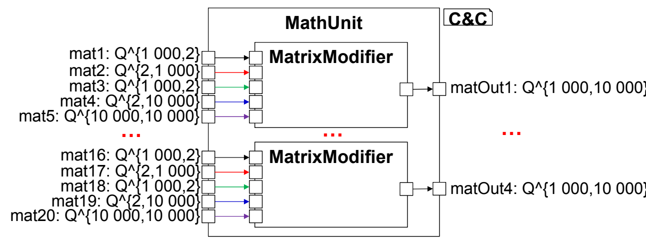


Figure 8: C&C architecture of a `MathUnit` component utilizing `MatrixModifier` (Figure 7).

Therefore, the C++ generator should only parallelize calculation paths having a similar number of operations. In equation (8) it makes no sense to calculate $mat1 \cdot (mat2 \cdot mat3)$ on one core and $mat4 \cdot mat5$ on another one. The second core would theoretically perform 50 *thousand* times more operations than the first, thus spending most of the time in idle mode waiting for the second core to be finished before the last matrix multiplication can be executed. The best option for (8) is to let the C++ generator create one thread for the entire computation and let the BLAS library create multiple threads for its matrix additions and multiplications.

However, the `MathUnit` component in Figure 8 contains four independent calculation paths, namely the four `MatrixModifier` subcomponents, each performing the same amount of calculations. Hence, it is advantageous to execute each subcomponent on its own core and to reduce the number of BLAS threads for each subcomponent; the reason is that a matrix multiplication distributed onto multiple cores needs more communication between the cores than the complete independent subcomponent calculations distributed onto multiple cores.

Sometimes, it is even better not to use multiple threads at all; if the computation bottlenecks are special hardware registers, e.g. *SIMD* units shared by all cores, threading would cause many L3 cache misses. For this reason, the EmbeddedMontiArc compiler toolchain can be configured via CLI to control the threading options for the C++ generator and for the BLAS libraries.

6 CASE STUDY

Our case study utilizes the following four C&C models:
(i) `ObjectDetector` with four `SpectralClusterer` subcomponents
(ii) `ObjectDetectorManOpt` is a manually optimized version of (i) to accelerate runtime performance in *MATLAB*
(iii) `ObjectDetectorLight` is (ii) without the `kmeans` operation
(iv) `MathUnit` with four `MatrixModifier` subcomponents.

The object detector C&C models (i)-(iii) consist of four `SpectralClusterer` subcomponents assuming that a vehicle has a camera on each side. The incoming images are clustered to detect objects, pedestrians, or other cars.

Model (i) contains the original formula of the spectral clusterer used in [41]. In contrast, model (ii) contains manually optimized code of the `NormalizedLaplacian` subcomponent to speed up the calculation significantly; this version is the Asad Ali's optimized *MATLAB* code [3]. In addition to our real-world examples (i) and (ii), the C&C model (iii) was created to have also a comparison with tools not supporting the `kmeans` operation. The model (iv) is our synthetic`MathUnit` C&C example from Section 5.

For each of these four example applications (i)-(iv) this case study executes the following experiments:
(a) measure effect of algebraic optimization on runtime speed
(b) evaluate impact of math backends on runtime performance
(c) compare runtime of code compiled with *EmbeddedMontiArc*, *Simulink*, *OpenModelica*, and *Java* with time interpreting it in *MATLAB*, or *Octave*
(d) measure web-browser performance running WebAssembly code produced by our compiler against handwritten MathJS code
(e) check EMA, Simulink, and Modelica model sizes versus Java, *MATLAB*, and JavaScript program length.

Figure 10 (a) shows that with a factor between 8 and 10 the algebraic optimizations of our toolchain based on mathematical domain knowledge deliver the largest impact on the runtime performance. Adding threading optimization for the `MatrixModifier` model has nearly no impact. For the `ObjectDetector` model the performance gain through threading is as little as 30%.

Figure 10 (b) shows the impact of using different mathematics libraries or frameworks in the compiled code. It is obvious that the *Octave* backend is always slower then *Armadillo*. The performance difference when executing the `MathUnit` model with the *Octave* backend instead of *Armadillo* however is quite small as for normal matrix addition and multiplication operations *Octave* offers native C++ functions, whereas other functionality in *Octave* is defined via m-code and must be interpreted at runtime. Executing all three `ObjectDetector` examples with the *Octave* backend takes significantly more time than executing these models with the *Armadillo* backend; the main reason is that eigenvalue and element-wise inverse square-root (2) calculations are much slower in *Octave* than equivalent native C++ implementations used by *Armadillo*.

The experiment showed that the *Blas* library performs multi-threading automatically. Using it we were not able to measure any improvement when letting our toolchain create multiple threads for the subcomponents of `MatrixModifier` and `SpectralClusterer`. Therefore we aggregated the results for the *Blas* backend in the column `Armadillo (Blas) 1/4 Threads` in Figure 10 (b). Another finding of the experiment was *Blas* being faster than *OpenBlas* for basic matrix operations such as multiplying and adding matrices. In contrast, the *OpenBlas* library is faster for more complex matrix operations such as eigenvalue calculation or matrix inversion. For this reason *Armadillo (Blas)* turns out to be the best library when compiling the `MathUnit` model whereas *Armadillo (OpenBlas)* is the best option for translating all object detector models to native Windows applications.

To compare the runtime performance of the compiled *EmbeddedMontiArc* native Windows 64-bit code with the compiled native code produced by other existing tools, programming languages or libraries **we modeled/programmed all four applications in *Simulink*[36], *OpenModelica*[15] with *OMEdit*[5], *Java* using *RelativeGPS*[2] library, *JavaScript* using *MathJS* [32], and as m-code for *MATLAB* [33] and *Octave* [40] again**.

The *MATLAB* code for the `ObjectDetectorManOpt` model was already given and we did not modify it to have an evaluation with an application not created by us. The *EmbeddedMontiArc* code contains exactly the same matrix operations (also in the same order) as they are present in the downloaded m-files from the MathWorks website. The only difference is that *EmbeddedMontiArc* groups functionality into components instead of functions and interaction takes place via connectors and not via function calls. The *Simulink* and *OpenModelica* code is a 1:1 mapping (of the syntax) of the *EmbeddedMontiArc* code, as all three tools are based on the C&C paradigm. The *Java* and the *JavaScript* applications are based on the *MATLAB* code as all the three are imperative programming languages.

Figure 9 contains selected model and code snippets showing how we remodeled the functionality in different tools/languages. In the left top part ① the `SpectralClusterer` subsystem with all its subcomponents is depicted. The two listings below contain the code of the atomic `MATLAB Function` block types: ② shows the original code used in the publication to model the behavior of the `NormalizedLaplacian` block, and ③ presents the manually algebraically optimized code (based on the fact that the `degree` matrix is a diagonal one, and therefore the power and matrix multiplication operations can be accelerated). The `ObjectDetector` application uses ②, whereas the `ObjectDetectorManOpt` and `ObjectDetectorLight` applications use the optimized one ③. The code in ② and ③ is the same as used in the m-files for the corresponding applications. Only the additional expression `nLaplacian = zeros(2500, 2500)` must be added when using the *MATLAB* code in *Simulink* as the MathWorks embedded coder needs the exact matrix dimensions for C code generation.

The middle part in Figure 9 represents the *OpenModelica* implementation of the `SpectralClusterer` component. The graphical model shown in ④ the *structural view* in *OMEdit* must not be consistent with the semantics of the textual Modelica model, since input and output ports are only visible in the graphical model if the textual one is enriched with the correct annotations (see small text snippets in ⑤). In our opinion the graphical annotations created by *OMEdit* pollute the textual *Modelica* model so that it becomes harder to read; a better solution would be to generate the graphical layout based on the defined in- and output ports or to store the graphical information in an additional file via tagging [17, 31]. The middle bottom listing ⑤ is the *Modelica* text code equivalent to the *MATLAB*/*Simulink* code shown in ②.

In contrast to the left and middle part in Figure 9 where the spectral clusterer was modeled as a C&C architecture, the code snippets on the right illustrate how to implement the spectral clusterer in an imperative programming language. The *MathJS* code ⑥ is the equivalent to the *MATLAB* code in ③; same holds for the middle right *Java* code ⑦. The *JavaScript* code ⑥ is very similar to the *MATLAB* code, as both are untyped languages. On the other hand, the *Java* code in ⑥ is strongly typed, cf. line 2 where the matrix is first created with its full-defined dimensions. Compared to equivalent *MATLAB* code ② or the equivalent *EmbeddedMontiArc*

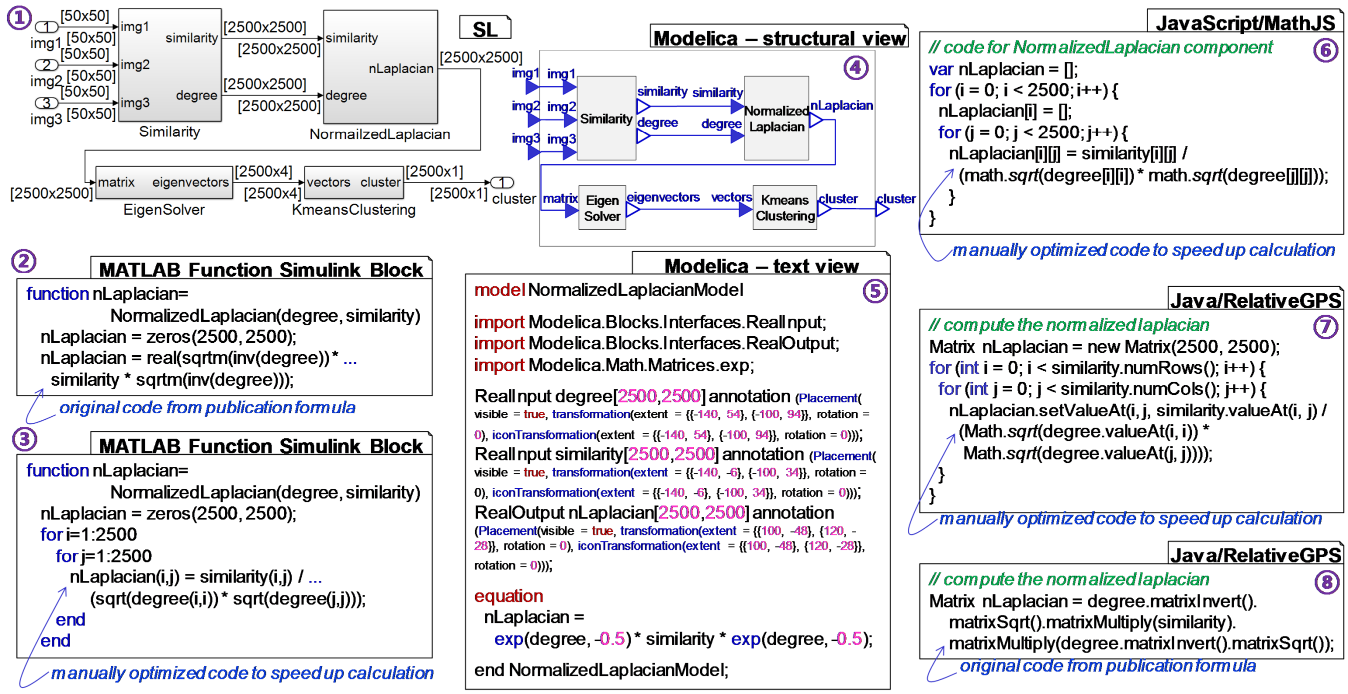


Figure 9: Model Snippets for SpectralClusterer component being modeled in Simulink and Modelica Code Snippets for SpectralClusterer component using JavaScript/MathJS and Java/RelativeGPS

code in Figure 3 (b), the optimized *Java* code ⑧ is cumbersome to read having no support for operator overloading - the mathematical infix expressions must be implemented using the cascade pattern (method chaining). In contrast to ② *MATLAB/Simulink* [35] *EmbeddedMontiArc* (Figure 3 (b)) also supports the matrix power operation for non-integer exponents if both the matrix and the exponent are real; therefore in *EmbeddedMontiArc* the short-form `degree^-.5` can be used whereas in *Simulink/MATLAB* the long and cumbersome syntax `sqrtm(inv(degree))` must be used.

As the model and code snippets in Figure 9 suggest that the imperative scripting languages need the least lines of code to develop the functionality, Figure 10 (e) substantiates this fact showing that *JavaScript* and *MATLAB* need the least amount of code to implement the four applications. The C&C languages *EmbeddedMontiArc* and *Simulink* (where besides the number of *MATLAB* lines of code also the numbers of in-/outport blocks, subsystems and other atomic blocks as well as the number of signal lines to connect two port blocks with each other need to be counted as *Simulink* is not completely text-based) need nearly the same amount of code/modeling elements as Java does. Due to their verbose syntax and annotations, *OpenModelica* models are the largest ones being more than twice as large as *EmbeddedMontiArc* or *Simulink* models and almost ten times as large as the textual scripting models of *MathJS* and *MATLAB*.

Figure 10 (c) shows the runtime duration to execute the applications with other frameworks. The *Octave* interpreter executed the same m-files as the *MATLAB* interpreter. The difference between the duration of the *Octave* interpreter and the *Octave* backend is that the *Octave* backend executed our algebraic optimized code on four parallel threads, and the *Octave* interpreter interprets the m-file in one thread according to the Windows Task Manager. For the `MathUnit` application, the *EmbeddedMontiArc* compiled code gets executed over 80 times faster than the interpreted m-file code by *Octave* or *MATLAB*. Since the non-optimized compiled code has a shorter execution time than the interpreted code (1.8s, see Figure 10 (a)), we assume that this time overhead is caused by the fact that the interpreter must parse all m-files and that since version R2015b *MATLAB* must decide whether it uses its Just-In-Time compiler producing C++ native code [46] or interpreting the statements which in turn results in expensive operations. For the `ObjectDetector` the compiled code is about six times faster than executing the m-file via the *MATLAB* command-line. The efficiency of *MATLAB* compared to *Octave*, both interpreting the same m-file, is probably due to the fact that MATLAB also recognizes that our `degree` matrix is sparse and then uses the backslash operator to invert the matrix by solving linear equations [34]. During the execution of our case study we found it remarkable that *MATLAB* can interpret the `MathUnit` model via m-file; but if the same model is remodeled in *Simulink* using the *Simulink* `MatrixMultiply` subsystems to multiply matrices we get the following compile error: *The Jacobian elements number of 'MatrixModifier' exceeds 2 147 483 647, the maximum Jacobian elements allowed in memory* (see screenshot from [14]). This means *Simulink* cannot be used as compiler for models dealing with large matrices. Also *OpenModelica* could not execute the `MathUnit` example as it crashed with an out of memory error message on a machine with 16 GB memory.

Figure 10 (d) shows the execution duration for the applications in the web browser when translating the *EmbeddedMontiArc* models

	(a) Effect of Optimizations			(b) Effect of Math-Backend			(c) Runtime on Windows 64-bit						(d) Runtime in Web Browser		(e) Lines of Code /Number of Characters (SL: Components/Ports/Connectors/LoC/#Chars)					
Model	No Optimization	Algebraic Optimization 1 Thread	Algebraic Optimization 4 Threads	Armadillo (OpenBlas) 4 Threads	Armadillo (Blas) 1/4 Threads	Octave 4 Threads	EMA-Compiler (native code)	Simulink	Open Modelica	Matlab-Interpreter	Octave-Interpreter	Java (Relative GPS)	EMA-Compiler (WASM)	JavaScript (MathJS)	EMA	Simulink	Open Modelica	Matlab	Java (Relative GPS)	JavaScript (MathJS)
(i)Object Detector	163s	17s	12s	12s	90s	896s	12s	> 20 min	-	143 s	41 min	-	322s	-	91/ 2 622	12/32/ 36/41/ 1 076	208/ 11 995	41/ 954	-	-
(ii)Object Detector ManOpt	16s	16s	10s	10s	68s	1004s	10s	28.6s	-	41s	56 min	-	176s	-	91/ 2 631	12/32/ 36/47/ 1 145	211/ 12 012	42/ 1 014	-	-
(iii)ObjectDetectorLight	16s	16s	10s	10s	67s	996s	10s	28.2s	-	41s	56 min	595s	175s	-	91/ 2 603	12/32/ 36/47/ 1 130	213/ 12 037	41/ 988	122/ 2 866	25/ 685
(iv)Math Unit	9.1s	1.8s	1.4s	1.4s	1.2s	1.3s	1.2s	-	-	9.2s	7.8s	-	2.2s	>25 min	45/ 1 217	8/30/ 33/0/0	110/ 7 281	11/ 157	57/ 1 049	12/ 205

Figure 10: Runtime and Code Statistics

to *WebAssembly* versus a direct *MathJS* implementation. While the C&C compiled model of the `ObjectDetectorLight` finished its execution in about 6.5 minutes in *Chrome* 66 (64-bit version), the calculation of the same functionality developed in *JavaScript* using the *MathJS* library needed more than half an hour where we stopped the evaluation. The original `ObjectDetector` could not be implemented in *MathJS* straightforward as in contrast to *EmbeddedMontiArc* and *MATLAB* this library offers no `k-means` clustering. This case study shows that it is possible to develop computationally expensive applications for the browser target with the *EmbeddedMontiArc* toolchain.

The runtime measurements of Figure 10 (c) and (d) were executed on an *Intel Core i7-6700HQ* quad core laptop with 2.6GHz clock speed and *Hyperthreading* support running *Windows 10 Professional 64-bit*; further software used includes: *MATLAB R2018a* (64-bit), *OpenModelica v1.12.0* (64-bit), *Octave 4.2.1* (64-bit), *Armadillo* version 8.200.2, *GCC* 7.1, *clang* 1.37.36 (64-bit), *emscripten 1.37.36*, *OpenBlas* version 0.2.20, and *CLAPACK* [10] 3.2.1 (containing *Blas* and *Lapack*).

The presented case study showed that *EmbeddedMontiArc* enables model driven development on a functional level where the modeler must only care about the domain to be modeled and can leave the implementation and the optimization details over to the proposed toolchain. In comparison to existing C&C tools like *Simulink* and *OpenModelica*, *EmbeddedMontiArc* models are small regarding the code size. The here presented compiler toolchain produces fast executable native code. The *EmbeddedMontiArc* compiler is the only one in the field producing portable code capable of dealing with matrices of millions of elements such as in our `MatrixModifier` example. Although *MATLAB* was able to handle the problem, as well, the code cannot be redistributed without the *MATLAB* environment itself. *Simulink, OpenModelica*, and *Java* failed due to internal restrictions, or deficient memory management. Furthermore, not all languages support complex operations such as k-means clustering. This case study also showed that our compiler produces astonishingly fast code running in web-browsers without the need to adapt the *EmbeddedMontiArc* models.

7 CONCLUSION

Component and connector (C&C) models, with their corresponding code generators, are widely used in the automotive industry. This paper presented a highly optimizing and multi-target C&C compiler for the component and connector modeling language *EmbeddedMontiArc*, which enables calculations on ultra large matrices occurring in real-world machine learning applications such as object detection and map transformations.

Due to the domain driven type system of *EmbeddedMontiArc* focusing on algebraic matrix properties, instead of only reusing the existing byte-based type systems with `int`, `double`, or `byte`, better algebraic optimizations based on mathematical matrix theory are possible.

The case study showed that the toolchain built upon these algebraic optimizations produces not only theoretically faster executable code, but indeed delivers an outstanding performance for existing real-world applications. Some computationally heavy calculations were only possible with the here presented C&C compiler.

The *EmbeddedMontiArc* modeling methodology focuses primarily on using mathematical algorithms directly from scientific publications. The main aim is to release the modeler from making decisions on how to rewrite the mathematical program in order to ensure runtime efficiently. This paper was a first step further into this direction.

Finally this paper also showed that for executing a modeling language efficiently much more than just a code generator is required; tasks such as including the correct runtime libraries and configuring the used compiler infrastructure with the correct parameters must be supported by the tooling, since all of these decisions may have a large impact on the runtime performance when executing the models of your new modeling language.

Acknowledgements This research was supported by a Grant from the GIF, the German-Israeli Foundation for Scientific Research and Development, and by the Grant SPP1835 from DFG, the German Research Foundation.

REFERENCES

[1] 2012. A decade of agile methodologies: Towards explaining agile software development. *Journal of Systems and Software* 85, 6 (2012), 1213 – 1221.

[2] 2014. Accurate Real-Time Relative Localization Using Single-Frequency GPS. In *The ACM Conference on Embedded Networked Sensor Systems (SenSys '14)*. ACM, ACM, Memphis, TN, USA. https://doi.org/10.1145/2668332.2668379

[3] Asad Ali. 2010. Spectral Clustering Algorithms. https://de.mathworks.com/matlabcentral/fileexchange/26354-spectral-clustering-algorithms.

[4] William F Ames. 2014. *Numerical methods for partial differential equations*. Academic press.

[5] Syed Adeel Asghar, Sonia Tariq, Mohsen Torabzadeh-Tari, Peter Fritzson, Adrian Pop, Martin Sjölund, Parham Vasaiely, and Wladimir Schamai. 2011. An open source modelica graphic editor integrated with electronic notebooks and interactive simulation. In *8th International Modelica Conference (Modelica'2011), Dresden, Germany, March 20-22, 2011*. Linköping University Electronic Press, 739–747.

[6] J. F. Bastien. 2017. WebAssembly 1.0: Threads. https://github.com/WebAssembly/design/issues/1073

[7] Christian Berger. 2016. An Open Continuous Deployment Infrastructure for a Self-driving Vehicle Ecosystem. In *IFIP International Conference on Open Source Systems*. Springer, 177–183.

[8] Vincent Bertram, Shahar Maoz, Jan Oliver Ringert, Bernhard Rumpe, and Michael von Wenckstern. 2017. Component and Connector Views in Practice: An Experience Report. In *Conference on Model Driven Engineering Languages and Systems (MODELS'17)*. IEEE, 167–177.

[9] Moritz Borgmann. 2006. Matrix Taxonomy. https://www.nari.ee.ethz.ch/teaching/ha/handouts/linalg3p.pdf.

[10] clapack 2018. CLAPACK (f2c'ed version of LAPACK). http://www.netlib.org/clapack/.

[11] Baran Dalgic. 2018. EmbeddedMontiArc with ROS connector for Gazebo simulator. https://youtu.be/DNtrR6mxxsk

[12] Bernard Desgraupes. 2013. Clustering indices. *University of Paris Ouest-Lab Modal'X* 1 (2013), 34.

[13] John W. Eaton, David Bateman, Søren Hauberg, and Rik Wehbring. 2016. *GNU Octave version 4.2.0 manual: a high-level interactive language for numerical computations*. http://www.gnu.org/software/octave/doc/interpreter

[14] Bernhard Rumpe Michael von Wenckstern Evgeny Kusmenko, Sascha Schneiders. 2018. Supporting materials for this paper including source code, models, and videos. http://www.se-rwth.de/materials/ema_compiler/

[15] Peter Fritzson, Peter Aronsson, Adrian Pop, Hakan Lundvall, Kaj Nystrom, Levon Saldamli, David Broman, and Anders Sandholm. 2006. OpenModelica-A free open-source environment for system modeling, simulation, and teaching. In *Computer Aided Control System Design, 2006 IEEE International Conference on Control Applications*. IEEE, 1588–1595.

[16] Filippo Grazioli, Evgeny Kusmenko, Alexander Roth, Bernhard Rumpe, and Michael von Wenckstern. 2017. Simulation Framework for Executing Component and Connector Models of Self-Driving Vehicles. In *Proceedings of MODELS 2017. Workshop EXE (CEUR 2019)*.

[17] Timo Greifenberg, Markus Look, Sebastian Roidl, and Bernhard Rumpe. 2015. Engineering Tagging Languages for DSLs. In *18th ACM/IEEE International Conference on Model Driven Engineering Languages and Systems, MoDELS 2015, Ottawa, ON, Canada, September 30 - October 2, 2015*. 34–43.

[18] Malte Heithoff. 2018. Modeling PacMan with EmbeddedMontiArc. https://youtu.be/GS2dqNFUpIE

[19] Steffen Hillemacher, Stefan Kriebel, Evgeny Kusmenko, Mike Lorang, Bernhard Rumpe, Albi Sema, Georg Strobl, and Michael von Wenckstern. 2018. Model-Based Development of Self-Adaptive Autonomous Vehicles using the SMARDT Methodology. In *Proceedings of the 6th International Conference on Model-Driven Engineering and Software Development (MODELSWARD'18)*. SciTePress, 163 – 178.

[20] R Hoekema, GJM Huiskamp, TF Oostendorp, GJH Uijen, and A van Oosterom. 1995. Lead system transformation for pooling of body surface map data: a surface Laplacian approach. *Journal of electrocardiology* 28, 4 (1995), 344–345.

[21] Franz E Hohn. 2013. *Elementary matrix algebra*. Courier Corporation.

[22] Katrin Hölldobler and Bernhard Rumpe. 2017. *MontiCore 5 Language Workbench*. Shaker.

[23] Petyo Ilov. 2018. Simulating several Cars. https://youtu.be/OFXWg8o3ni8

[24] National Instruments. 1998. *BridgeView and LabView: G Programming Reference Manual*. Technical Report 321296B-01. National Instruments. 667 pages.

[25] MKL Intel. 2007. Intel math kernel library. (2007).

[26] David Koufaty and Deborah T Marr. 2003. Hyperthreading technology in the netburst microarchitecture. *IEEE Micro* 23, 2 (2003), 56–65.

[27] Evgeny Kusmenko, Alexander Roth, Bernhard Rumpe, and Michael von Wenckstern. 2017. Modeling Architectures of Cyber-Physical Systems. In *European Conference on Modelling Foundations and Applications (ECMFA'17) (LNCS 10376)*. Springer, 34–50.

[28] Chris Lattner and Vikram Adve. 2004. LLVM: A compilation framework for lifelong program analysis & transformation. In *Proceedings of the international symposium on Code generation and optimization: feedback-directed and runtime optimization*. IEEE Computer Society, 75.

[29] Mike Lorang. 2017. Evolutionary Tuning of PID Controllers. https://youtu.be/7llpVLklnPY

[30] Ranjan K Mallik. 2001. The inverse of a tridiagonal matrix. *Linear Algebra Appl.* 325, 1-3 (2001), 109–139.

[31] Shahar Maoz, Jan Oliver Ringert, Bernhard Rumpe, and Michael von Wenckstern. 2016. Consistent Extra-Functional Properties Tagging for Component and Connector Models. In *ModComp*.

[32] MathJS. 2018. MathJS. http://mathjs.org/.

[33] Mathworks. 2018. *MATLAB Mathematics*. Technical Report R2018a. MATLAB & SIMULINK. 684 pages. https://de.mathworks.com/help/pdf_doc/matlab/math.pdf

[34] MathWorks. 2018. Matrix Inverse - MATLAB Documentation. https://de.mathworks.com/help/matlab/ref/inv.html.

[35] MathWorks. 2018. Matrix Power - MATLAB Documentation. https://de.mathworks.com/help/matlab/ref/mpower.html - C/C++ Code Generation.

[36] Mathworks. 2018. *Simulink User's Guide*. Technical Report R2018a. MATLAB & SIMULINK. 4212 pages. http://www.mathworks.com/help/pdf_doc/simulink/sl_using.pdf

[37] Pedram Mir Seyed Nazari. 2017. *MontiCore: Efficient Development of Composed Modeling Language Essentials*. Shaker Verlag.

[38] Armin Mokhtarian. 2018. Modeling an Autopilot for Self-Driving Cars with EmbeddedMontiArc. https://youtu.be/i4DWrKFC9j4

[39] Mozilla. 2018. WebAssembly 1.0: Browser compatibility. https://developer.mozilla.org/en-US/docs/WebAssembly

[40] Sandeep Nagar. 2018. *Introduction to Octave: For Engineers and Scientists, volume 1 of 1*. Apress.

[41] Andrew Y Ng, Michael I Jordan, and Yair Weiss. 2002. On spectral clustering: Analysis and an algorithm. In *Advances in neural information processing systems*. 849–856.

[42] Morgan Quigley, Ken Conley, Brian Gerkey, Josh Faust, Tully Foote, Jeremy Leibs, Rob Wheeler, and Andrew Y Ng. 2009. ROS: an open-source Robot Operating System. In *ICRA workshop on open source software*, Vol. 3. Kobe, Japan, 5.

[43] Jon Reid. 2015. Are Slow Tests Killing Your Feedback Loop. https://qualitycoding.org/slow-tests/

[44] Conrad Sanderson and Ryan Curtin. 2016. Armadillo: a template-based C++ library for linear algebra. *Journal of Open Source Software* (2016).

[45] J. Shi, J. Wan, H. Yan, and H. Suo. 2011. A survey of Cyber-Physical Systems. In *2011 International Conference on Wireless Communications and Signal Processing (WCSP)*. 1–6. https://doi.org/10.1109/WCSP.2011.6096958

[46] Loren Shure. 2016. Run Code Faster With the New MATLAB Execution Engine. https://blogs.mathworks.com/loren/2016/02/12/run-code-faster-with-the-new-matlab-execution-engine/.

[47] Richard M Stallman. 2002. GNU compiler collection internals. *Free Software Foundation* (2002).

[48] Miroslaw Staron. 2017. *Detailed Design of Automotive Software*. Springer International Publishing, Cham, 117–149. https://doi.org/10.1007/978-3-319-58610-6_5

[49] Ulrike Von Luxburg. 2007. A tutorial on spectral clustering. *Statistics and computing* 17, 4 (2007), 395–416.

[50] Michael von Wenckstern. 2018. EmbeddedMontiArcStudio: Overview Video. https://youtu.be/VTKSWwWp-kg

[51] W3C. 2018. WebAssembly 1.0. http://webassembly.org.

[52] W3C. 2018. WebAssembly 1.0. http://webassembly.org/docs/dynamic-linking/.

[53] Endong Wang, Qing Zhang, Bo Shen, Guangyong Zhang, Xiaowei Lu, Qing Wu, and Yajuan Wang. 2014. Intel math kernel library. In *High-Performance Computing on the Intel Xeon Phi*. Springer, 167–188.

[54] Henning Witzel. 2018. Valley of Fire State Park, Moapa Valley, United States. http://finda.photo/image/15989

[55] Zhang Xianyi, Wang Qian, and Werner Saar. 2016. OpenBLAS: An optimized BLAS library. *Accedido: Agosto* (2016).

[56] Alon Zakai. 2011. Emscripten: an LLVM-to-JavaScript compiler. In *Proceedings of the ACM international conference companion on Object oriented programming systems languages and applications companion*. ACM, 301–312.

[57] Yuefeng Zhang. 2004. Test-driven modeling for model-driven development. *IEEE Software* 21, 5 (Sept 2004), 80–86. https://doi.org/10.1109/MS.2004.1331307