RHEA: A Reactive, Heterogeneous, Extensible, and Abstract Framework for Dataflow Programming

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Abstract

Robotics and IoT applications are perfect candidates that can benefit from the functional reactive programming paradigm. Moreover, since a typical program can be represented as a dataflow graph, the application can be conceptually separated and distributed in different machines and the several graph partitions can run in parallel and possibly in different execution stacks. In this paper we propose a general-purpose reactive framework that can express complex applications, seamlessly and transparently integrating different sources and middlewares. The framework is abstract and extensible, making it easy to integrate with well-established technologies that rely on the PubSub model. We demonstrate the usability of the framework by providing application examples in the domain of robotics and IoT.

CCS Concepts • **Software and its engineering → Data flow architectures**; **Data flow languages**;

Keywords dataflow programming, stream processing, functional reactive programming (FRP), declarative languages, implicit concurrency, node placement

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1 Introduction

A typical application in robotics or Internet of Things (IoT) needs to timely and continuously respond to time-varying external sensory data and, as a result, the reactivity of these applications is imperative. Typically, the programmer of such applications has to deal with asynchronous callbacks in conventional imperative programming languages, in order to implement tedious and often error-prone behaviours that should comply with the reactive requirements.

A promising and relatively recent proposal for simplifying the implementation of reactive applications is *functional reactive programming* (FRP) [7]. FRP makes heavy use of higher-order functional operators to define, essentially, a dataflow network of processing nodes. These high-level abstractions alleviate, as intended, the low-level implementation chores. Although FRP was originally proposed as a framework for developing graphical user interfaces, the key high-level abstractions are generic enough that other domains can benefit from this approach. As a result of its generality and its increasing popularity several general-purpose implementations emerge with different capabilities and prerequisites.

It is natural, therefore, to investigate whether robotics and IoT applications can fit into this new paradigm. Indeed, most robotic applications follow the Robot Perception Architecture, where inputs to system are the robot's sensors, which are then processed by a dataflow graph, whose output is given as commands to the robot actuators. Moreover, robotics typically involve several different other robotic or IoT systems to enhance their sensing abilities. These combined applications make more evident issues of distributing the dataflow graph to several robotic units and issues of heterogeneity and interoperability between different middlewares and protocols.

The first steps towards using FRP in robotics was identified in [9] and realized in Yampa[1], an FRP framework developed in Haskell. Yampa provides its functionality through

[1] https://wiki.haskell.org/Yampa

an embedded DSL, as is customary for many of the FRP libraries. Although an interesting proposal, there is limited acceptance from the robotics community, mainly because it does not integrate well with existing well-established robotics middlewares such as the Robot Operating System (ROS) [17]. As a result, legacy algorithms should be written from scratch in this new library. Moreover, it does not assume integration with other reactive systems via the Reactive Streams Standard (RSS)[2] which is essential for applications that need multiple heterogeneous sources.

Motivated by the robotics and IoT community we propose RHEA, an abstract FRP general-purpose framework that aims to act as a unifying layer that can be mapped and executed using different reactive libraries and existing middlewares such as ROS and MQTT[3]. The programmer can transparently express complex reactive applications within this framework that may use both sensing from several robots and IoT sensors. The framework places the dataflow nodes to computational resources and handles the serialization needed between different execution engines.

The rest of the paper is structured as follows. Section 2 provides some background context about dataflows and the state-of-art middlewares used in robotics and IoT. Section 3 presents the framework's architecture and capabilities. Section 4 discusses implementation details followed by Section 5 which presents several optimizations that have been implemented in the framework. Section 6 demonstrates some use-cases of the framework mainly motivated by robotics and IoT. Section 7 discusses related work and finally Section 8 concludes with future directions.

2 Background

In this section we provide some necessary background context. In particular, we briefly present the dataflow model and the notation of graphs we use in the remaining sections. We continue with a brief overview of the well-established middlewares used in robotics and IoT, namely the Robot Operating System (ROS) and the Message Queuing Telemetry Trasport (MQTT) protocol. For the rest of the paper we assume however familiarity with functional reactive programming (FRP).

2.1 The Dataflow Computational Model

In the dataflow computational model, the program is represented as a dataflow graph, where nodes are independent computational units and edges are communication channels between these units. A node is fired immediately when its required inputs are available and therefore no explicit control commands are needed for execution. An immediate consequence is that the nodes of the graph can run independently and potentially in parallel as soon as their inputs are present.

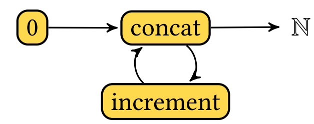


Figure 1. Natural numbers

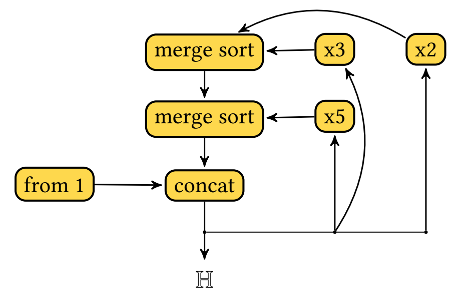


Figure 2. Hamming numbers

Figure 1 shows a dataflow graph enumerating the set $\mathbb{N}$ of natural numbers. In the dataflow graph above, we can discern three types of nodes: sources, which do not have any incoming edge and act as value generators to initiate computation, sinks, which do not have any outgoing edges and inner nodes, which transform one or more incoming streams and redirect their output to other nodes. The *zero* node just produces a stream with a single value 0 and then terminates. *Concat* produces a single stream by concatenating the stream produced by *zero* and *increment*, while *increment* transforms its input stream by adding one to its values. Finally, the sink node displays the result, which is the stream of natural numbers.

Streams can be infinite, such as the stream produced by *concat* because it is the concatenation of a single-value stream and an infinite one. Moreover, the graph is cyclic as *concat* feeds input to *increment* and vice versa. The most interesting fact is that there nodes are independent and therefore can run in parallel. For instance, while *increment* is processing value 5 (i.e. to produce value 6), the previous result (i.e. value 5) passes through *concat* to reach the sink node, which can concurrently process it to display it.

As a more involved example, consider the problem of enumerating the *Hamming numbers*, which are generated by the mathematical formula $\mathbb{H} = 2^i 3^j 5^k$, where $i, j, k \in \mathbb{N}$. Figure 2 depicts an intuitive dataflow solution to the above problem, borrowed from the book of Lucid [19].

Dataflow graphs can be executed both in a single machine and in a cluster of machines where each node can be

[2] http://www.reactive-streams.org
[3] http://mqtt.org/

placed in a different machine. A possible single-machine implementation could represent edges as in-memory queues, whereas a multi-machine one could realize them as channels between TCP sockets, allowing communication across the network.

2.2 Robotics and IoT Middlewares

In the following we briefly present the ROS and MQTT, the de-facto middlewares used in robotics and IoT. The architecture of both follow a topic-based publish-subscribe (PubSub) pattern to loosely couple different processes and at the same time maximize flexibility.

2.2.1 ROS

ROS is an open-source middleware for robot software, which emphasizes large-scale integrative robotics research [17]. It provides a *thin* communication layer between heterogeneous computers, from robots to mainframes and it has been widely adopted by the research community around the world, due to its flexibility and maximal support of reusability through packaging and composability. It provides a compact solution to the development complexity introduced by complex robot applications that consist of several modules and require different device drivers for each individual robot.

It follows a peer-to-peer network topology, implemented using a topic-based *PubSub* messaging protocol and its architecture reflects many sound design principles. Another great property of *ROS* is that it is language-agnostic, meaning that only a minimal specification language for message transaction has been defined, so contributors are free to implement small-size clients in different programming languages, with *roscpp* for C++ and *rospy* for Python being the most widely used ones.

A typical development scenario is to write several *nodes*, that subscribe to some topics and, after doing some computation, publish their results on other topics. The main architectural issue here is that subscribing is realized through asynchronous callback functions, so complicated schemes easily lead to unstructured code, which obviously lead to unreadable and hard-to-maintain code. Our approach gives a solution to the aforementioned problem.

2.2.2 MQTT

Internet of Things (IoT) conveys the concept of a multitude of heterogeneous devices, ranging from low-cost sensors to vehicles with embedded electronics, are connected and provide the ability to collect data and exchange it amongst themselves. The development of such systems though, due to their heterogeneity, is rather complex and costly. Recent development of a variety of middleware frameworks, showed that a standard protocol of communication is imperative along with supporting tools [15].

The most widely spread protocol is *MQTT*, which follows the *PubSub* messaging pattern and provides a very minimal and lightweight communication layer in order not to put a strain on the resource-bounded system [13]. For instance, an *IoT* application could connect to some sensors by subscribing to their corresponding topics, taking decisions that would result in some commands to some actuators, by publishing to their corresponding topics.

Fortunately, the dataflow model seems to be rather fitting for these scenarios [4], as every node in the graph is completely independent, and consequently can be any "*thing*". This useful property of the model makes it a good architectural choice for such applications. The only thing to consider is how these things will communicate in a standard way, so as to be able to add new types of *things* and integrate it in an effortless way to an existing dataflow network.

3 The RHEA Framework

In this section, we set out our main design goals and provide an overview of the system architecture and the DSL.

3.1 Requirements and Objectives

The proposed system should be *reactive*, relying solely on asynchronous message-passing for inter-component communication leading to loose coupling, isolation, location transparency and error propagation.

One of the major concerns while designing the framework was the ability to deploy it anywhere, from low-cost robots to mainframes. Apparently such attribute would require a very flexible runtime environment that have the ability to handle *heterogeneous* devices.

As the new technologies and frameworks arise the system should be able to adapt and be extended in order to remain useful and general-purpose. Therefore, careful consideration was taken to compose the system of different independent modules, which could *extensible* and easily modified. With that concept in mind, generality and abstraction were heavily emphasized during both the design and the implementation process.

The framework should be also *abstract* in terms of implementation details, as it is completely agnostic of any machine-specific requirements. It is designed as a unifying conceptual base for further extensions and careful consideration was taken not to restrict it in any aspect.

3.2 Architecture

The RHEA framework consists of several clearly separated modules, whose interconnection is illustrated in Figure 3.

A typical workflow of the system is as follows. The user writes a program in the provided domain-specific language, which constructs an internal representation of the dataflow graph. Afterwards, using information about the available resources in the network, the constructed graph is optimized

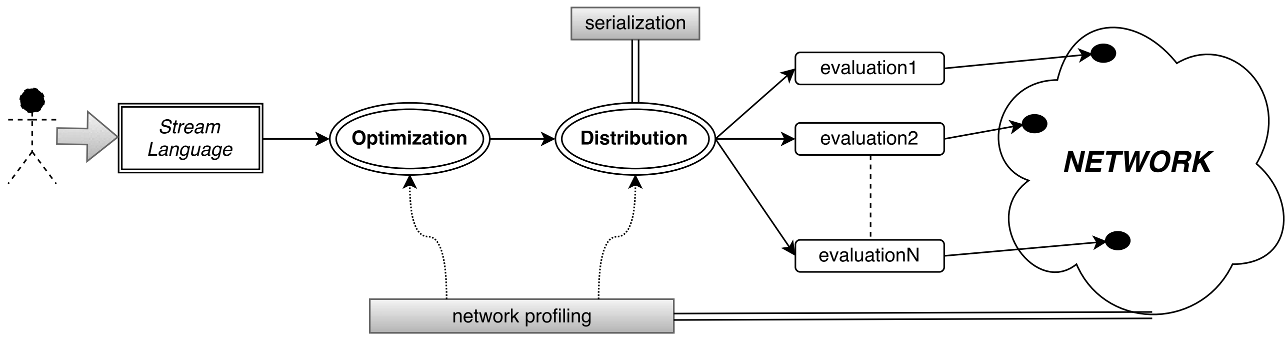


Figure 3. System architecture

and partitions of the graph are assigned to physical computational resources. The optimized graph partitions are then distributed across the available machines for execution, maybe using a different evaluation strategy each time.

More specifically, a flexible evaluation strategy was employed where different executors can be considered when available. This design satisfies the requirements of extensibility, heterogeneity and abstraction of the system since each partial graph can be evaluated by a different EvaluationStrategy which could interpret it using a specific streams library or even compile into CUDA code for execution on a GPU. In Section 4 we provide three different evaluation strategies.

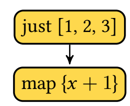
3.3 Dataflow Graphs

We will now present the graph construction using the DSL of RHEA and demonstrate the key supported features of the available operators. We opted to do that by illustrative examples, rather than providing a formal specification. While the examples are written in Java, any other JVM language would do.

The kind of dataflow graph that can be expressed using the framework's stream language are directed cyclic graphs with possibly many inputs and outputs. The data channels (i.e. edges of the dataflow graph) are represented using the Stream data type, which is parametric, meaning that it can emit values of any data type, whether built-in or user-defined. The stream produced may terminate, successfully or erroneously, or even be infinite.

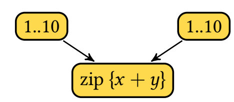
The construction of the internal dataflow graph is implicit, through a rich set of operators on the Stream data type. Each Stream object contains internally a dataflow graph of type FlowGraph, which is only to be accessed and manipulated by the internal module, evaluation strategies and optimizers. Therefore, an application developer only needs to work with the Stream type.

Source nodes are constructed using built-in functions of the Stream type. For instance, Stream.just(1,2,3) produces the stream that emits just the values 1, 2 and 3. The return variable of this creation function is an object of type Stream.




```
Stream.just(1, 2, 3)
      .map(x -> x + 1);
```

Figure 4. Single input processing node




```
Stream.zip(
   Stream.range(1, 10),
   Stream.range(1, 10),
   (x, y) -> x + y);
```

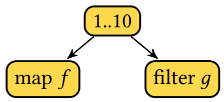
Figure 5. Multiple input processing node

Processing nodes can be divided into two classes: *single input* ones and *multiple input* ones. Single input nodes are inserted into an existing Stream object, by calling an operator on that object. Multiple input nodes are constructed by built-in function that take as argument already existing Stream objects.

Figure 4 shows an example of a single input node, namely that of map, which transforms the input stream (i.e. just the values 1, 2 and 3) by applying a user-defined function to every emitted value. Figure 5 shows an example of a multiple input node, namely that of zip, which transforms the input streams by applying a user-defined function to each emitted pairs of values. Here we also see the stream creation function Stream.range.

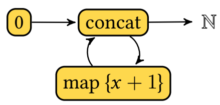
The variables returned by all processing nodes are Stream objects. These objects can be reused in different parts of the graph to enable splitting a node's output to different processing nodes or outputs. Figure 6 shows such an example, where the filter operator only emits values for which the given function returns true.

Cycles are constructed using the loop operator, which is a single input processing node. It requires a function that, given an input stream, constructs a subgraph that redirects its output to that input, therefore creating a feedback loop. Figure 7 shows an example of the loop operator to represent the natural numbers, just as the graph shown earlier in




```
Stream<Int> st = Stream.range(1, 10);
st.map(f).print();
st.filter(g).print();
```

Figure 6. Split example




```
Stream
    .just(0)
    .loop(s -> s.map(i -> i + 1));
```

Figure 7. Cyclic example

Figure 1. The concat operator is a multiple input node that concatenates its input streams.

Lastly, to evaluate a given dataflow graph and do something with its output values, we need to call the subscribe method of the Stream object and pass as argument a user-defined action (i.e. function with side-effects).

4 Implementation

Since extensibility is a major design priority, most individual critical components are defined using the Strategy design pattern, isolating the desired functionality in a separate interface and allowing the system to select the appropriate instantiating classes at runtime. The main pluggable components of the system, for which default implementations are already provided by the current implementation as separate libraries, are *Evaluation*, *Optimization*, *Distribution*, *Serialization* and *Network Profiling*. The source code for all RHEA components is publicly available on Github[4].

Every value passed through the framework's streams is wrapped inside a Notification object, which discriminates stream values into three categories: onNext (when the stream provides a regular value), onError (when an error occurs) and onComplete (when the stream completes its output). This enables the system to gracefully handle error propagation.

In order to make the framework easy to integrate with other stream and dataflow technologies, every input and output node implements the interfaces that RSS defines, namely the Publisher and the Subscriber interface. This also enables users to define new types of sources or sinks, in order to integrate the framework with other general technologies (e.g. system events, HTTP requests, PubSub implementations, etc). In particular, a sink node (output) should implement the Subscriber interface, which essentially defines three methods corresponding to reactions to a Notification, one for each of the categories mentioned above. Moreover, a source node (input) should implement the Publisher interface, which defines a single method subscribe(Subscriber), where a Subscriber requests the Publisher to start emitting values.

Many existing technologies provide these interfaces, or at least adapters from their internal representations, and therefore they are very easy to be integrated to the framework.

4.1 Execution

Every primitive operator corresponds to an expression implementing the Transformer interface and a complete dataflow is defined by a Stream variable and an object implementing the Output interface, which can be either an Action, a Sink or a list of these.

Roughly speaking, the EvaluationStrategy interface accepts the Stream variable and its corresponding Output and executes it, however desired. The strategies we have implemented so far follow:

RxJavaEvaluationStrategy which uses RxJava [5], an established and well-maintained library for asynchronous programming using the *Observable* type, which is very close, semantically, to our *Stream* type.

RosEvaluationStrategy which integrates the *ROS* middleware into the framework. This strategy's main objective is to set up a *ROS* client and configure every RosTopic used within the dataflow that needs to be evaluated to use this client. After that, evaluation is propagated to a generic strategy, for example, to RxJavaEvaluationStrategy.

MqttEvaluationStrategy which integrates the MQTT middleware into the framework, in the same way *ROS* is integrated.

4.2 Distributed Execution

An evaluation strategy executes the requested dataflow graph in a single machine, without concern about distribution and resource utilization. For distribution and cluster management, one needs to implement the DistributionStrategy interface by adjusting the granularity (i.e. size) of the graph to evaluate to fit the available resources (see, Section 5) and partition it across all computational resources, maybe using different evaluation strategies.

The default DistributionStrategy uses the *Hazelcast*[6] library to discover and manage multiple machines and used its internal decentralized PubSub model to communicate intermediate results across the network. Figure 8 illustrates the partitioning of a dataflow graph over several machines, where each machine – except the last one – outputs its result to a Hazelcast topic, from which another machine gets its input.

[4] https://github.com/rhea-flow

[5] http://github.com/ReactiveX/RxJava

[6] http://hazelcast.org/

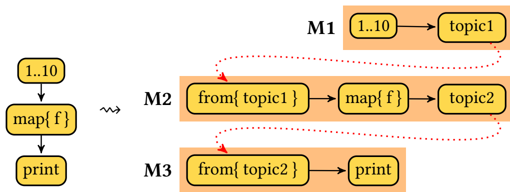


Figure 8. Partitioning

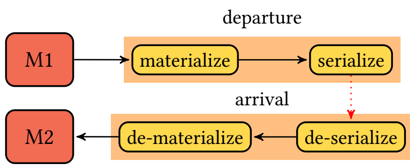


Figure 9. Serialization process

According to the distribution strategy being used, the available machines will require a certain initial configuration. For the Hazelcast case, a little piece of setup code needs to be executed on every member of the cluster, which is together with the main EvaluationStrategy class. Moreover, helpful information can also be added at this step, such as number of CPU cores. It is the distribution strategy's responsibility to ensure that this information is properly distributed and handled.

Apart from this initial configuration, the distribution strategy needs to enable members to declare certain capabilities that they possess, which are required by specialized nodes. For instance, a source node emitting values from a ROS topic must be executed on a machine having ROS installed, in order to set up a ROS client. The default implementation uses strings to represent capabilities and are declared in the initialization code of each machine separately.

4.2.1 Serialization

As communication between machines across a network is mandatory, data types emitted through the streams must be serialized on departure and de-serialized on arrival at each machine. For this reason, each DistributionStrategy must be configured with a class implementing the Serializer interface, but we also provide a default one that covers most datatypes. Figure 9 depicts the serialization process in more detail.

5 Optimizations

This section describes three stages of optimization that the dataflow graph goes through before being evaluated:

- proactive filtering that places filtering operations as soon as possible;
- granularity adjustment that combines adjacent operation into a single more efficient operation;

Figure 10. Take/skip/distinct before map

Figure 11. Filter before map

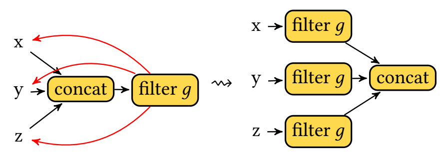


Figure 12. Filter/distinct before concat/merge

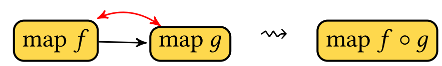


Figure 13. Merge maps

- and node placement that places nodes that should be collocated to the same machine.

The optimization phases run sequentially, that is the output of one phase becomes input of the next. The main purpose of the optimization graph is to achieve better performance and better utilization of the available resources.

5.1 Proactive Filtering

The first optimization stage is a heuristic one, based on the fact that if a filter operation can be moved earlier (i.e. closer to source nodes) while preserving the original semantics, then there will be benefit concerning computational cost and cross-machine communication overhead. Figures 10-12 illustrate one representative example of each general class of graph transformation.

5.2 Granularity Adjustment

Each different node of the dataflow graph will be executed on a separate thread/process. The fact that graphs can grow very big, for instance when programming a swarm of robots, poses a problem when available computational resources are limited. For this reason, the second optimization stage tries to adjust the granularity of the dataflow graph to a desired value, which is normally the number of available threads amongst all machines. To reach the desired granularity, the optimizer applies some semantic-preserving transformation, as shown in the figures 13-18.

In Figure 13 we merge two map operations into one map operation that uses the composition of the two initial functions, while in Figure 14 a map followed by a filter is substituted by a more complex equivalent operation, namely

Figure 14. Combine map with filter

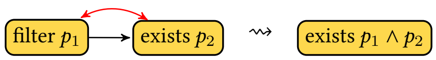


Figure 15. Combine filter with exists

Figure 16. Combine map with exists

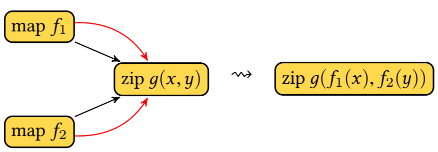


Figure 17. Combine map with zip

filterMap. In Figures 15 and 16 we apply some simple properties of the boolean functions involved to decrease the number of nodes. Lastly, in Figures 17 and 18 we utilize function composition to embed map operations into zip operations.

5.3 Node Placement

After the first two passes, we have an optimized dataflow graph with fine-tuned granularity. At this stage, nodes are mapped to tasks and are deployed across the available machines, keeping resource utilization in mind. If the desired granularity has not been reached yet, the DistributionStrategy applies fusion to pairs of tasks until it reaches it, as shown in Figure 19.

The final decision to be made is where each of these newly constructed tasks will be executed, although some of them need to necessarily be placed on specific machines with certain skills.

Apart from these hard constraints, we need to minimize communication overhead. For this purpose, one must implement the NetworkProfileStrategy by providing a way to calculate network distance between available machines, which is then fed as input to the NodePlacement optimizer.

6 Applications

This section provides two non-trivial example applications, in order to demonstrate the expressiveness of our DSL. While we have not deployed the code to actual robotic/IoT devices, we have tested them against real-time recorded data, which realistically emulate these devices.

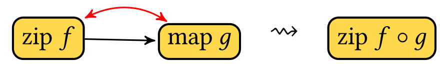


Figure 18. Combine zip with map

Figure 19. Task fusion

6.1 Robot Control Panel

This application concerns real-time monitoring of a robot, that is publishing its information and sensor-data to ROS topics, through a graphical user interface (GUI).

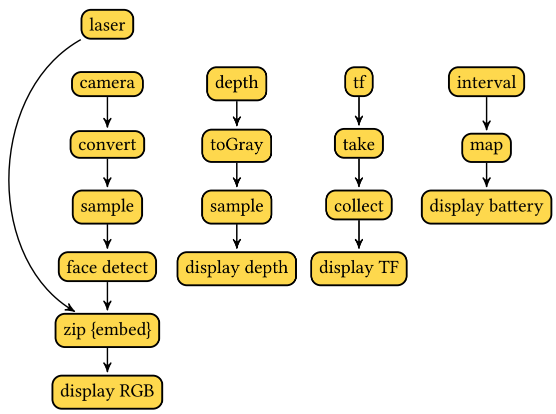
The /camera/rgb topic provides the frames of the robot's camera as coloured images, while the /camera/depth provides frames that provide depth information. The /tf topic publishes parent-child relations of the internal topics of the robot's configuration, and finally the /scan/ topic provides information from the robot's laser that gives horizontal depth information in polar coordinates.

The GUI displays the laser data embedded on the camera stream, while allowing for real-time face detection. Additionally, it displays the depth frames and the tf relations as a tree. Finally, a mock-up battery bar is displayed to showcase the framework's ability for simulation. Figure 20 illustrates the dataflow solution to the above problem and its corresponding RHEA code.

The implementation details (i.e. the visualization class and methods faceDetect (line 6), embedLaser (line 7) and toGray (line 14) are not shown for brevity's sake. It is worth noting that this model of programming encourages a clean separation of concerns between the individual components, namely between the sensor data manipulation and the actual visualization on the GUI.

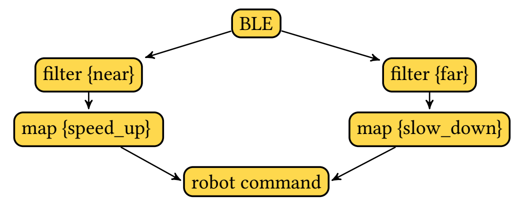
6.2 Robot Hospital Guide

As a final example, we will examine a combined application that involve both robotics and IoT. Consider a robot that guides patients to different parts of a hospital, such as the gym or cafeteria. We assume also that the map localization, path finding and obstacle avoidance are already implemented and provided by default by ROS. The problem is to calibrate the robot's speed according to the patient's status. In order to keep track of the patient's distance from the robot, each patient carries a smartphone that acts as a bluetooth low-energy (BLE) beacon. The robot uses its bluetooth receiver to publish the distance from the signal source to an MQTT topic, which is then transformed by our stream application to velocity commands for the robot, in the form of slowing down or speeding up.




```
Stream<LaserScan> laser = Stream.from(new RosTopic<>("/scan"));
Stream<Mat> image =
    Stream.<Image>from(new RosTopic<>("/camera/rgb"))
          .map(CvImage::toCvCopy)
          .sample(100, TimeUnit.MILLISECONDS)
          .map(this::faceDetect);
Stream.zip(laser, image, this::embedLaser)
      .subscribe(viz::displayRGB);
Stream.from(new RosTopic<>("/tf"))
      .take(50)
      .collect(HashMap::new, (m, msg) -> ...)
      .subscribe(viz::displayTF);
Stream.<Image>from(new RosTopic<>("/camera/depth"))
      .map(this::toGray)
      .sample(100, TimeUnit.MILLISECONDS)
      .subscribe(viz::displayDepth);
Stream.interval(2, TimeUnit.SECONDS)
      .map(v -> (100 - v) / 100.0)
      .subscribe(viz::displayBattery);
```

Figure 20. Robot control panel




```
Stream.configure(new HazelcastDistributionStrategy(
          RxjavaEvaluationStrategy::new,
          RosEvaluationStrategy::new,
          MqttEvaluationStrategy::new));

Topic<RobotCommand> vel = new RosTopic<>("/robot/cmd");

Stream<Proximity> ble = Stream.from(new MqttTopic<>("/ble"));

ble.filter(Proximity::isNear)
    .map(d -> Commands.SPEED_UP)
    .subscribe(vel);

ble.filter(Proximity::isFar)
    .map(d -> Commands.SLOW_DOWN)
    .subscribe(vel);
```

Figure 21. Hospital guide: Robot control

```
Stream.configure(new HazelcastDistributionStrategy(
          RxjavaEvaluationStrategy::new,
          MqttEvaluationStrategy::new));

Stream.from(ReactiveBeacons.observe())
          .map(Beacon::getProximity)
          .subscribe(new MqttTopic<>("/ble"));
```

Figure 22. Hospital guide: RxJava-MQTT integration

The first module constitutes the main program logic, where a declared dataflow graph acts as a stream transformation from beacon information to velocity commands to the robot. Figure 21 shows the dataflow graph with its corresponding RHEA code.

The second module (Fig. 22) uses the library *ReactiveBeacons*[7] to get a stream of beacon data via RxJava, and then publishes it to a MQTT topic, which is the input of the first module. This example showcases the framework's ability to combine different technologies and act as a high-level, declarative unified layer.

7 Related Work

7.1 Dataflow Systems

The necessity for implicit parallelism and distribution of more and more applications, dealing with huge and/or complex data, has brought increasingly more attention to the dataflow programming model. Nowadays there are various implementation of dataflow systems focused on different applications such as Big Data batch and stream processing, Machine Learning and others. In the following we discuss the prominent dataflow systems and the similarities and differences with the proposed framework RHEA.

The two most prominent dataflow framework for scalable large-data processing is Apache Spark [20] and Apache Flink [3]. Both support a rich set of data-parallel operators and can be used for either batch or stream processing. They follow the same general approach as RHEA by implicitly creating a dataflow pipeline. It is also worth noting that Apache Flink optimizes the dataflow graph by applying semantically-equivalent graph rewriting [10]. Apart from these similarities there are also key differences. They focus on providing a full execution stack and therefore they do not provide the flexibility in using existing underlying system to perform execution. They accomplish distributed execution by partitioning on the data in contrast to RHEA that partitions the graph on the operations.

Similar to the flexibility that RHEA aims to provide is the project Apache Beam [2], formerly known as Cloud Dataflow and an evolution of FlumeJava [5]. Apache Beam shares the same key idea with RHEA namely they provide a unified abstract programming layer for batch and stream processing that can use multiple executors. They provide, for instance, an Apache Spark and an Apache Flink executor. However, we assume that the cluster is homogeneous and

[7] http://github.com/pwittchen/ReactiveBeacons

thus the whole program is executed using a single executor. Another framework that shares the same similarities with Apache Beam and RHEA is dispel4py [8], a Python framework that focuses on scientific workflows. It provides the ability to describe abstract workflows for distributed data-intensive applications. Similar to the RHEA evaluation strategy concept, it allows different mappings to enactment systems, such as MPI and Apache Storm. However, it does not tackle heterogeneity issues and simultaneously executing graph partitions to different enactment systems.

Another dataflow framework from Google is TensorFlow [1], which is an open-source polyglot library for machine intelligence and especially construction of neural networks. Tensorflow differs from the aforementioned dataflow systems since it assumes that data are Tensors, namely multi-dimensional arrays, the nodes operate in Tensors and the program is a dataflow network of such operations. Tensorflow is similar to RHEA since it is inherently heterogeneous by considering different hardware devices such as CPU and GPUs. Moreover, it provides distributed execution by partitioning the dataflow graph similarly to what RHEA is proposing. The main difference compared to RHEA approach is that the system is not reactive, therefore it is not optimized for asynchronous stream of events.

Regarding the reactive-aware systems, RxJava and AkkaStreams are the most mature frameworks that support programming languages that target the JVM. It is worth mentioning *Akka* [8] which is the foundation library where AkkaStreams relies on. In particular, Akka is a toolkit and runtime for highly concurrent, distributed and resilient message-driven applications and its execution model follows the Actor model. In this model one perceives abstract computational agents, called actors, that are distributed in space and communicate with point-to-point messages. In reaction to a message, an actor can create more actors, make local decisions, send more messages and determine how to respond to the next message received. Similar to the problem of *ROS* that our framework solved, using Actors can be daunting. AkkaStreams try to provide a higher-level abstraction from the Actor model and specifically it provides a convenient API for stream processing and also dataflow graph construction. The difference with RHEA is that AkkaStreams solely relies on Akka. On the other hand, RHEA offers the ability to choose between several evaluation strategies to match the application's needs.

Is is also worthwhile to mention *Ziria*, a dataflow DSL for wireless systems programming, which manages to replace low-level code with high-level declarative code without loss of performance [18].

[8] http://akka.io

7.2 Robotics and IoT

It is only natural that the dataflow model would make its way through the field of robotics, as many behaviours in control theory are expressed as dataflow diagrams.

Roshask [6] is a binding from the Haskell programming language to the basic *ROS* interfaces. Like RHEA, the approach is to overcome the shortcomings of *ROS* callbacks by viewing topics as streams. This allows for, and encourages, a higher level of abstraction in robot programming, while making the fusing, transforming and filtering of streams fully generic and compositional. RHEA and *roshask* were heavily influenced by the work of Hudak's group (Yale Haskell Group) on robot DSLs and FRP in general [7, 9, 16]. *Yampa* [9] is a DSL embedded in Haskell that realizes the FRP model, using arrows to minimize time and space leaks.

IoT applications often deal with much heterogeneity, due to the variety of sources that different devices introduce. Therefore, a component-based approach suits well to solve this problem and there are some dataflow frameworks that follow that approach. Another interesting *IoT* framework that follows a dataflow approach is *Node-RED* [4], which is a visual tool for wiring together hardware devices, APIs and online services in new and interesting ways. Applications called flows, are built immediately on a browser, and can be deployed on the Cloud with just a single click. The main advantage of this tool is that it encourages social development, due to the fact that flows are stored in JSON format, which can be easily imported and exported for sharing with others.

8 Conclusions and Future Work

The framework described in this paper offers a unified and extensible way for reactive applications to be developed. Primarily motivated by the well-established middlewares in robotics and IoT, the main focus of the framework is extensibility and heterogeneity. To that end, a constant effort to generalize and make components as abstract as possible was made.

The applications demonstrated the framework's ability to provide a higher level of abstraction, where the language only specifies how different components coordinate, without knowledge of the implementation details. Like *Ziria*, our belief is that certain domains have fixated their methods on low-level programming, whereas more satisfactory paradigms can solve many shortcomings.

The set of operators aided expressibility, making it possible to specify any dataflow graph in a concise and readable manner. This disallowed optimizations suitable for less expressive models, but recent research suggest that general dataflow topologies have optimization opportunities that are yet to be found [10]. In the current reincarnation of the framework only a minimal optimization stage has been implemented, which nevertheless paves the path to more advanced optimization techniques, such as the stream fusion techniques proposed in [11] and [12], as well as those used in Apache Flink [10].

Apart from a more sophisticated optimization phase that can be investigated as a future direction, there are also other extensions that are equally interesting and challenging. Again motivated by the robotics domain, an interesting extension is to apply dynamic reconfiguration where the applications operate in environments that are constantly changing. For instance operating in an environment where battery powered robots participate or the connectivity of the cluster is unstable. Adaptive techniques for reconfiguring the dataflow graph distribution should be devised in such situations. Morover, these environments give rise to fault-tolerant execution and it is certainly challenging to propose methods for graceful recovery.

Lastly, another interesting future direction is alternative techniques regarding node placement. It is worth investigating techniques that use reinforcement learning to decide a reasonably efficient node placement, as recently proposed in [14].

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