Generalized Graph Connections for Dataflow
Modeling of DSP Applications

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Abstract—In dataflow representations for signal processing systems, applications are represented as directed graphs in which vertices represent computations and edges correspond to buffers that store data as it passes between computations. The buffers are single-input, single-output components that manage data in a first-in, first-out (FIFO) fashion. In this paper, we generalize the concept of dataflow buffers with a concept called “passive blocks”. Like dataflow buffers, passive blocks are used to store data during the intervals between its generation by producing actors, and its use by consuming actors. However, passive blocks can have multiple inputs and multiple outputs, and can incorporate operations on and rearrangements of the stored data subject to certain constraints. We define a form of flowgraph representation that is based on replacing dataflow edges with the proposed concept of passive blocks. We present a structured design methodology for utilizing this new form of signal processing flowgraph, and demonstrate its utility in improving memory management efficiency, and execution time performance.

I. INTRODUCTION

Dataflow modeling is widely used in design processes and tools for signal processing systems. In this form of modeling, applications are represented as directed graphs, called dataflow graphs, in which vertices (actors) represent discrete computations that are executed iteratively (fire) to process semi-infinite streams of input data. Each edge e = (x, y) in a dataflow graph represents a logical communication channel between actors x and y. More specifically, each e = (x, y) represents a first-in, first-out (FIFO) buffer that stores data during the period between its production by actor x and its consumption by actor y. Actors can be fired when certain conditions, referred to as firing rules, are satisfied [1].

Dataflow modeling has proven to be of great utility in the design and implementation of signal processing systems for various reasons, including its provisions for ensuring determinacy, support for exploiting parallelism, and capability for exposing high-level application structure that is useful for many kinds of design optimization beyond those associated with exploiting parallelism [2].

A limitation of signal processing dataflow representations, however, is that they are inefficient in describing inter-actor communication patterns that depart from the simple single-input, single-output (SISO) interface and FIFO behavior that are defined for dataflow edges. As a canonical example of this kind of inefficiency, consider the fork actor illustrated in Figure 1a. This is a synchronous dataflow (SDF) [3] actor that consumes a single token t and produces two tokens — one on each output edge — on each firing. The values of the two tokens that are produced are identical to the value of the input token t. Thus, this actor can be viewed as providing a kind of broadcast functionality.

Figure 1b shows a pseudocode fragment for the fork actor. From this pseudocode, we can see that there is overhead of copying the value of the input token to each of the outputs. This overhead in general includes a run-time cost as well as a cost in terms of increased memory requirements. The overhead is required under a pure dataflow interpretation since the input token must be replicated on each of the two output edges (FIFOs).

The functionality of the fork actor can be realized more efficiently if we abandon this pure dataflow interpretation, and implement the actor instead using the one-input, two-output component illustrated in Figure 1c. This component, which we refer to here as a passive fork, is not fired as a dataflow actor is. Instead, the component operates in a manner similar to a typical FIFO implementation, where a buffer is associated with the component, and tokens are written to and read from the buffer using write and read pointers, respectively. However, the passive fork has two read pointers — one corresponding to each output edge of the fork actor — instead of the single read pointer that would be used in a FIFO. In effect, we

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have transformed the fork actor, which operates in an “active” manner (by firing) into an passive component, which is used by writing to and reading from the component’s ports.

A more powerful form of this “active-to-passive” conversion is illustrated on Figure 14, which shows a gain actor that is connected at the input of the fork actor. This gain actor corresponds to a constant multiplication, where the constant factor $k$ is a parameter of the actor. The gain together with the fork can be replaced by a single passive component. This component is similar to the passive fork actor, except that when a value is written into the buffer, it is multiplied by $k$ before being stored. In this paper, we generalize this process of converting certain kinds of actors into passive components, which achieve equivalent functionality through read/write interfaces rather than through the mechanism of being fired. This generalization leads to a powerful new design methodology in which passive components of arbitrary complexity can be designed to provide streamlined functionality for actors or subgraphs that are more efficiently realized with internal buffers and read/write interfaces. When dataflow graphs are transformed to incorporate such passive components, we refer to the resulting graphs as Passive-Active Flow Graphs (PAFGs). A central objective of this paper is to introduce PAFGs as a useful new representation for model-based design of signal processing systems.

II. RELATED WORK

Many researchers have investigated efficient buffer memory management in dataflow graphs (e.g., see [2], [4]–[6]). Bhattacharya and Lee discussed the concept that certain actors, such as the fork actor described above, can be implemented more efficiently by deviating from pure dataflow semantics [7]. However, this earlier work did not propose any approach for integrating such deviations systematically into the modeling framework. In this new work, we develop such a systematic approach based on the novel abstraction of PAFGs.

Perhaps the most closely related form of dataflow memory management optimization to what we develop in this paper is buffer merging, which involves merging subsets of input and output buffers of a given actor to a common memory space (e.g., see [8], [9]). Like the method of [9], the PAFG approach allows for memory sharing across arbitrary numbers of input and output buffers for a given actor. Similarly, like the method of [8], the PAFG approach does not involve expansion to a single rate rate graph, which can be costly in terms of compiler memory requirements and time complexity for highly multirate applications (e.g., see [10]). In this sense, the PAFG approach provides a novel combination of useful features in the two previously developed buffer merging approaches described above. Additionally, while the methods of [8], [9] are limited to SDF graphs, the PAFG approach is not restricted to any specific form of dataflow. For example, Boolean dataflow switch and select actors [11] can be formulated as optimized PAFG components using the same methodology that is presented in this paper. Applicability beyond SDF is also a distinguishing point compared to the abstraction of deterministic SDF with shared FIFOs (DSSF) [12].

While there are significant differences between buffer merging, DSSF, and PAFG-based memory management, investigating and exploiting complementary relationships among the different approaches is an interesting direction for future work.

III. PAFG REPRESENTATIONS

In this section, we develop in detail the PAFG model of computation. In this work, PAFGs are derived from dataflow graphs, and are intended as intermediate representations or implementation architectures for dataflow application graphs (dataflow models of signal processing applications). For concreteness, we develop the concepts of PAFGs here in the context of core functional dataflow (CFDF) as the application graph model; however, the concepts are not specific to CFDF and can be adapted to other forms of dataflow. CFDF is a highly expressive model that can be used to represent other well-known dataflow models, including synchronous, cyclo-static, and Boolean dataflow [13]. CFDF is the model that underlies the lightweight dataflow environment (LIDE) tool [14], which we use for our experiments in Section V.

We first define some notation that will be useful throughout the remainder of this paper. Given an edge $e$ in a directed graph, we denote the source and sink vertices of $e$ by $src(e)$ and $snk(e)$, respectively. A self-loop is an edge whose source and sink vertices are identical. In the remainder of this paper, we consider only directed graphs that do not contain self-loops. Self-loops can be incorporated easily into the methods developed in this paper; we omit the details due to space limitations.

Given an edge $e$, we say that $src(e)$ is a predecessor of $snk(e)$, $snk(e)$ is a successor of $src(e)$, and $src(e)$ and $snk(e)$ are adjacent vertices. The sets of all predecessors and successors of a vertex $v$ in a given graph are denoted by $pred(v)$ and $succ(v)$, respectively. The sets of all input edges and output edges of $v$ are denoted by $in(v)$ and $out(v)$, respectively.

We refer to PAFG vertices as blocks. In a dataflow graph, vertices correspond to computational modules, and edges correspond to SISO buffers between the modules. In contrast, in a PAFG, both computational modules and buffers are represented as vertices, and edges represent connections between computational modules and buffers. Additionally, PAFG buffers are not restricted to SISO interfaces — they can have multiple inputs, multiple outputs, or both. A third distinguishing characteristic of the PAFGs that we are interested in this paper is that they are bipartite graphs. We define this bipartite characteristic precisely in Section III-C.

For conciseness and clarity, we assume that dataflow graphs and PAFGs are directed graphs rather than multigraphs (which can contain multiple edges directed in the same direction and between the same pair of vertices). The adaptation of the PAFG model to multigraphs can be readily achieved when implementing the model.

We refer to an ordered pair of actors $(d, yd)$ as a dataflow pair and an ordered pair of PAFG blocks $(b, yb)$ as a PAFG pair.
The PAFGs that we are concerned with in this paper are derived from corresponding dataflow graphs (application graphs). We elaborate on the process of deriving a PAFG from a dataflow graph in Section III-D. This derivation process places blocks in a PAFG \( F \) in correspondence with actors or edges in the dataflow graph from which \( F \) was derived. A \textit{simple passive buffer} is a PAFG block that corresponds in this way to an edge in some dataflow graph. A PAFG block that is not a simple passive buffer is referred to as a \textit{non-simple block}. We often refer to simple passive buffers as \textit{simple blocks}.

A. PAFG Blocks

A PAFG block is either a \textit{passive} block or an \textit{active block}. The distinction between these two types was motivated intuitively in Section I More precisely, an active block corresponds to an application graph actor that is used in the usual way — that is, through interfaces that are associated with firing the actor and (if available) for testing fireability. In CFDF, these are referred to as \textit{invoke} and \textit{enable} interfaces, respectively [13]. In contrast, a passive block is used through read/write interfaces, as illustrated by the passive fork example in Section I.

Given an application graph \( G \), we assume that implementations of the actors in \( G \) are available in an \textit{actor library}. We assume that each actor in \( G \) has one active implementation (with enable/invoke interfaces) in the library, and that it may or may not have a passive implementation (with read/write interfaces). We refer to an actor \( A \) as a \textit{buffer actor} if it has a passive implementation; otherwise, we refer to \( A \) as a computational actor. Thus, only buffer actors can be placed in correspondence with passive blocks.

Like active blocks, non-simple passive blocks correspond to actors. However, they are used (executed) in a different way — again, as illustrated by the difference between the active (“standard”) and passive versions of the fork actor in Section I. A non-simple passive block should implement the same input/output behavior as its corresponding actor — that is, it should perform the same mapping from input streams into output streams. For background on the interpretation of actors as mappings from input streams to output streams, we refer the reader to [1]. In this work, we assume that unit testing processes are used to validate such “mapping equivalence” between passive blocks and their corresponding actors. For background on synergies between unit testing and dataflow-based design processes, we refer the reader to [14]. We envision as an interesting area for future work the automation of the equivalence checking process between active and passive implementations of the same buffer actor.

A block in a PAFG is either a \textit{computational block} or a \textit{buffer block}. The computational BUFFER dichotomy is another relevant way to distinguish between blocks in addition to the active/passive and simple/non-simple dichotomies. All computational blocks are active blocks. However, buffer blocks can in general be either passive or active.

B. Coordination Functions and Alternating PAFGs

When deriving a PAFG, each buffer block needs to be designated as being an active or passive buffer. An active buffer is executed like any other actor (using enable/invoke interfaces), while passive buffers are read from and written to directly by computational blocks and active buffers (using read/write interfaces). Coordination functions are used to specify whether a given block is executed in a passive or active fashion. Thus, coordination functions specify how schedulers should manipulate the blocks when executing the associated application graph.

Given a PAFG \( F \), we represent the set of blocks (vertices) in \( F \) by \( \text{blks}(F) \), and we define a \textit{coordination function} of \( F \) as one that specifies for each block \( b \in \text{blks}(F) \) whether or not \( b \) is to be executed in an active or passive fashion. More precisely, a coordination function is a mapping \( C: \text{blks}(F) \rightarrow \{\text{pssv, actv}\} \), where \( C(b_c) = \text{actv} \) for every computational block \( b_c \in \text{blks}(F) \), and \( C(b_s) = \text{pssv} \) for every simple block \( b_s \in \text{blks}(F) \). We refer to \( C(b) \) as the \textit{coordination type} of block \( b \) with respect to \( C \). Computational blocks and simple blocks must be coordinated in an active and passive fashion, respectively, and a coordination function just “reminds us” of this. On the other hand, a coordination function \( C \) specifies for each non-simple buffer block whether or not the block is to be executed in a passive or active fashion (if we execute the PAFG based on \( C \)).

A coordinated PAFG is an ordered pair \( Z = (F, C) \), where \( F \) is a PAFG and \( C \) is a coordination function for \( F \).

C. Alternating PAFGs

In this work, we are interested in a specific form of coordinated PAFG, which we refer to as an \textit{alternating PAFG}. An alternating PAFG is defined to be a coordinated PAFG that is bipartite in terms of the active blocks and passive blocks. More precisely, an alternating PAFG \( Z = (F, C) \) with \( F = (V_f, E_f) \) is one that satisfies \( C(\text{src}(e)) \neq C(\text{snk}(e)) \) for all \( e \in E_f \).

A block in a PAFG is an \textit{interface block} if it has no output edges or it has no input edges. The concept of coordinated PAFGs allows for the possibility of interface blocks that are passive. However, we have not yet experimented with the design of passive interface blocks. Exploration into the utility of passive interface blocks appears to be an interesting direction for future work.

In our context, direct communication between pairs of active blocks or pairs of passive blocks is ambiguous. Intuitively, some form of buffer is needed to manage the flow of data between active blocks (just as dataflow edges connect pairs of communicating actors in dataflow graphs). Generalization of the developments of this paper beyond alternating PAFGs is potentially another interesting direction for future work.

D. Direct PAFGs

We propose a design methodology in which dataflow graphs are converted into a kind of equivalent PAFG representation, and then transformed so that some subset of the active buffers is converted into passive coordination form. In this section, we
define the equivalent PAFG representation, which we refer to as direct PAFG form, and in Section IV we define the process of transforming active buffers into passive form.

Suppose that we are given a dataflow graph \( G = (V, E) \). For each edge \( e \in E \), we define a corresponding passive buffer \( \rho(e) \). We denote the set of passive buffers defined in this way as \( P(G) \). Thus, \( P(G) = \{ \rho(e) \mid e \in E \} \). Each \( \rho(e) \in P(G) \) is a simple block (see Section III-A) since it is defined in correspondence with a distinct dataflow graph edge \( e \).

Similarly, for each \( v \in V \), we define a corresponding block \( \alpha(v) \). Each \( \alpha(v) \) is referred to as an actor block with corresponding actor \( v \). If \( v \) is a computational actor, then \( \alpha(v) \) is defined as a computational block. Otherwise, \( \alpha(v) \) is defined as a non-simple buffer block. For a given dataflow graph \( G = (V, E) \), we define the set of all actor blocks by \( A(G) = \{ \alpha(v) \mid v \in V \} \).

For each \( z = \rho(e) \in P(G) \), we define the PAFG pairs \( \kappa_i(z) = (\alpha(\text{src}(e)), z) \) and \( \kappa_o(z) = (z, \alpha(\text{snk}(e))) \). Recall that PAFG pairs are ordered pairs of blocks, and actor blocks and passive buffers both represent different types of blocks. Thus, \( \kappa_i(z) \) and \( \kappa_o(z) \) can correctly be referred to as PAFG pairs. The sets of all pairs defined in this way are represented by \( \kappa_i = \{ \kappa_i(z) \mid z \in P(G) \} \), and \( \kappa_o = \{ \kappa_o(z) \mid z \in P(G) \} \).

The direct PAFG representation of \( G \) is a coordinated PAFG \( Z_d = (F_d, C_d) \). The PAFG \( F_d = (V_d, E_d) \) is defined by \( V_d = (A(G) \cup P(G)) \) and \( E_d = (\kappa_i \cup \kappa_o) \), and the coordination function is defined by \( C_d(b) = \text{actv} \) for every non-simple block \( b \).

By construction, each edge in \( Z_d \) connects a simple block to a computational block or an active buffer block. Thus, a direct PAFG is always an alternating PAFG.

To illustrate key concepts introduced in this section, Figure 2 shows an example of a dataflow graph (application graph). Figure 3 shows the direct PAFG that results from this application graph, and Table I shows the coordination function for the direct PAFG. In Figure 2 and Figure 3, each \( H_i \) is a computational actor, each \( J_i \) is a buffer actor, each \( Y_i \) corresponds to \( H_i \), each \( Z_i \) corresponds to \( J_i \), and each \( L_i \) is a simple passive buffer.

As illustrated in Figure 2 and Figure 3, we use the convention that dataflow graph actors are drawn with circles, PAFG blocks are drawn with rectangles, and the borders of PAFG blocks are solid or dashed based on whether the blocks are active or passive, respectively.

![Fig. 2. A dataflow graph (application graph).](image)

![Fig. 3. The direct PAFG that is derived from the application graph of Figure 2.](image)

| Block (\(B\)) | Coordination type \(C(B)\) |
|--------------|--------------------------|
| \(Y_{i,k} = 1,2,\ldots,10\) | \text{actv} |
| \(Z_{j,j} = 1,2,\ldots,4\) | \text{actv} |
| \(L_{k,k} = 1,2,\ldots,15\) | \text{passv} |

E. Association between Dataflow Graphs and PAFGs

Given a dataflow graph \( G = (V, E) \) and a PAFG \( F = (V_f, E_f) \), we say that \( G \) and \( F \) are associated (each is associated with the other) if each simple block \( p \) in \( F \) corresponds to an edge \( e \) in \( G \) (\( p = \rho(e) \)), and each non-simple block \( q \) in \( F \) corresponds to an actor \( a \) in \( G \) (\( q = \alpha(a) \)). By construction, the direct PAFG representation of a dataflow graph \( G \) is always associated with \( G \).

IV. PASSIVIZATION TRANSFORMATION

In the direct PAFG representation of a dataflow graph, all non-simple buffer blocks are coordinated as active buffers. In this section, we define the process of converting an active buffer to passive form. This conversion process is defined as a transformation process for alternating PAFGs — that is, a process that takes as input an alternating PAFG and produces as output another alternating PAFG.

If \( b \) and \( c \) are adjacent blocks in a PAFG, then we disallow coordination functions that assign a passive form to both \( b \) and \( c \). We refer to this as the adjacent buffer coordination (ABC) restriction. We impose the ABC restriction because we do not have any mechanism defined for direct communication between two passive blocks. Intuitively, communication between passive buffer blocks “stalls” because each is “waiting” for a read or write operation to be initiated by the other. It may be interesting as future work to investigate communication mechanisms that allow one to relax the ABC restriction.

Given an alternating PAFG \( (F, C) \) and a block \( b \) in \( F \), we say that \( b \) is simply surrounded if all of its predecessors and successors are simple passive buffers. Formally, this means that \( x \) is a simple passive buffer for all \( x \in (\text{pred}(b) \cup \text{succ}(b)) \).

For example, in Figure 3 blocks \( Z_1 \) and \( Z_2 \) are simply surrounded, while blocks \( L_1 \) and \( L_2 \) are not.

Suppose that we have an alternating PAFG \( Z_a = (F_a, C_a) \), where \( F_a = (V_a, E_a) \), and suppose we have an active buffer \( \beta \in V_a \) that is simply surrounded. Then we can perform the passivization transformation of \( Z_a \) with respect to \( \beta \). This transformation, which is the primary contribution of this section, produces a new PAFG \( Z_b = (F_b, C_b) \), \( F_b = (V_b, E_b) \). The
vertex set of $F_b$ is defined by the set difference $V_b = V_a - V_z$, where $V_z = \text{pred}(\beta) \cup \text{succ}(\beta)$.

To define the edge set $E_b$, we first define the sets $Y_p = \{ y \in \text{pred}(x) \mid x \in \text{pred}(\beta) \}$, and $Y_s = \{ y \in \text{succ}(x) \mid x \in \text{succ}(\beta) \}$. Since $\beta$ is simply surrounded, we have from the ABC restriction that all elements of $Y_p$ and $Y_s$ are active blocks. Next, we construct the set $E_{\beta}$ of PAFG pairs that are directed from members of $Y_p$ to $\beta$, or from $\beta$ to members of $Y_s$: $E_{\beta} = \{ (\{ e, \beta \} \mid x \in Y_p) \cup (\{ \beta, y \} \mid y \in Y_s) \}$. We also define the set of all input and output edges of blocks that are adjacent to $\beta$: $E_{\beta} = \{ e \in \text{out}(x) \mid x \in V_z \} \cup \{ e \in \text{in}(x) \mid x \in V_z \}$. We can then define $E_b$ by $E_b = (E_{\beta} - E_{\beta}) \cup E_{\beta}$.

The coordination function $C_b : V_b \rightarrow \{ \text{pssv}, \text{actv} \}$ is derived by changing the form of $\beta$, while “copying” the values from $C_a$ for all other blocks in $V_b$: $C_b(\beta) = \text{pssv}$, and $C_b(x) = C_a(x)$ for all $x \in (V_b - \{ \beta \})$.

To summarize, the passivization transformation with respect to a simply surrounded active buffer $\beta$ involves the following steps: (1) changing the form of $\beta$ from $\text{actv}$ to $\text{pssv}$; (2) removing all of the predecessor and successor blocks of $\beta$ along with their input and output edges; (3) adding edges that are directed to $\beta$ from each member of $Y_p$; and (4) adding edges that are directed from $\beta$ to each member of $Y_s$.

The passivization transformation can be applied multiple times, where in each application (transformation step) after the first, the transformation is applied on the graph that results from the previous step.

For example, Figure 4 illustrates the PAFG that results after applying the passivization transformation three times on the direct PAFG of Figure 3. The transformation is applied with respect to $Z_1$, $Z_2$, and then $Z_3$.

V. Application Examples and Experiments

In this section, we present experiments on two relevant applications. These experiments demonstrate the utility of design optimization using PAFGs. In both of these experiments, we carried out a sequence of passivization transformations by hand, and implemented the original dataflow graph and the optimized PAFG (derived through the transformations) using the lightweight dataflow environment (LIDE) [14]. In this work, we have developed extensions in LIDE to provide complete support for design and implementation using PAFGs, including features that allow implementation and interfacing of non-simple passive blocks. The experiments for both applications are conducted on an Intel Core i7-2600K Quad-core CPU running Ubuntu Linux 16.04 LTS, and using GCC 5.4.0 for code compilation.

A. Error Vector Magnitude Computation

The error vector magnitude (EVM) is a figure of merit for signal quality in communication systems. EVM computation is an important application in measurement and test equipment for communications. For background on EVM computation, we refer the reader to [15].

A dataflow graph for measuring the EVM for a given reference signal and received signal is shown in Figure 5. This is a dynamic dataflow graph modeled using CFDF semantics, as supported in LIDE. Here, SRC1 provides on each ith firing the input data length for the ith EVM computation. The actors SRC2 and SRC3 provide the real and imaginary parts, respectively, of the reference signal; and similarly, SRC4 and SRC5 provide the real and imaginary parts of the received signal. The actor FA is a fork actor (see Section I), which broadcasts data to multiple output ports. The actors RFC and RCC are interleavers that interleave corresponding pairs of input tokens so that the real and imaginary parts of each signal sample are arranged in successive elements of the actors’ output streams. The actors $E$ and RFM compute the error vector and reference signal magnitude, respectively. The actor RMS computes the root mean square (RMS) $k_e$ of the error signal and the RMS $k_r$ of the reference signal, and derives the EVM result as the ratio $k_e/k_r$. The actors RFA and EA compute the average magnitudes of the reference and error signals, respectively. The SNK actor represents the output interface of the graph; in our experiments, we use a file writing interface.

We first derive a direct PAFG, which represents the implementation of the application graph (Figure 5) using pure dataflow semantics. To the direct PAFG, we apply the passivization transformation three times with respect to the actors FA, RFC and RCC. All three of these actors are simply-surrounded, and can be implemented efficiently in passive form.

The resulting optimized PAFG is illustrated in Figure 6. We use a minor abuse of notation where non-simple blocks in the PAFG are labeled with the same names as their corresponding actors in the application graph. Blocks labeled as SPB represent simple passive buffers.

Table II compares the performance of the direct and transformed PAFGs. Through passivization, the throughput is im-
TABLE II
RESULTS FOR THE EVM APPLICATION.

|                | Throughput (samples/sec) | BMR (MB) |
|----------------|--------------------------|----------|
| Direct PAFG    | $7.95 \times 10^5$       | 29.30    |
| Optimized PAFG | $1.05 \times 10^6$       | 21.97    |

B. Jitter Measurement Application

Jitter measurement is another important application for real-time signal processing in communication systems. In this section, we apply PAFG-based modeling and optimization for a jitter measurement system design that is presented in [16]. For details on this system design, including the dataflow model and the constituent actors, we refer the reader to [16].

An important parameter in the jitter measurement system is the window size, which determines the number of samples that are processed in a given dataflow graph iteration. Larger window sizes in general improve the throughput at the expense of a larger BMR [16].

Again, we first derive the direct PAFG and then transform this into an optimized PAFG through a sequence of passivization transformations. In this transformation process, we convert the six fork actors in the design, from active to passive buffer form. The resulting optimized PAFG is illustrated in Figure 7. In this figure, the non-simple passive blocks corresponding to the fork actors are denoted $F_1, F_2, \ldots, F_6$.

Table III shows the improvement measured from the optimized PAFG compared to the direct PAFG for different window sizes. From these results, we see significant improvements delivered by the optimized PAFG in terms of the trade-off between throughput and BMR. For the optimized PAFG, the BMR ranges from 0.38MB to 6.0MB for increasing window sizes, and the throughput ranges from $1.9 \times 10^6$ samples/sec to $3.1 \times 10^6$ samples/sec.

TABLE III
RESULTS FOR THE JITTER MEASUREMENT APPLICATION.

| Window size | Throughput | BMR |
|-------------|------------|-----|
|             | (samples/sec) | (MB) |
| Direct PAFG | $7.93 \times 10^5$ | 29.30 |
| Optimized PAFG | $1.05 \times 10^6$ | 21.97 |

VI. CONCLUSION AND FUTURE WORK

In this paper, we have introduced passive-active flow-graphs (PAFGs) as a model of computation that complements dataflow models for design and implementation of signal processing systems. PAFGs generalize the concept of dataflow edges into multi-input, multi-output components that are called “passive blocks”. PAFGs provide a new approach to integrating designer-specified memory management optimization systematically into the framework of dataflow-based design and implementation. In addition to presenting details of the PAFG model of computation, we have introduced the passivization transformation, which can be used iteratively to derive progressively more efficient PAFGs. We have demonstrated the utility of PAFGs and the passivization transformation on two important signal processing applications. Useful directions for future work include automating the equivalence checking between active and passive versions of a given actor, and the generalization of relevant methods in this paper beyond alternating PAFGs.

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