High-Level Workflow Interpreter for Real-Time Image Processing

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Abstract: Medical imaging is used in clinics to support the diagnosis and treatment of diseases. Developing effective computer vision algorithms for image processing is a challenging task, requiring a significant amount of time invested in the prototyping phase. Workflow systems have become popular tools as they allow the development of algorithms as a collection of function blocks, which can be graphically linked to input and output pipelines. These systems help to improve the learning curve for beginning programmers. Other systems make programming easier and increase productivity through automatic code generation. VGLGUI is a graphical user interface for image processing that allows visual workflow programming for parallel image processing. It uses VisionGL functions for automatic wrapper code generation and optimization of image transfers between RAM and GPU. This article describes the high-level VGLGUI workflow interpreter and demonstrates the results of two image processing workflows.

1 INTRODUCTION

Medical imaging is used in clinics to support the diagnosis and treatment of diseases (Queirós et al., 2018). There is a recent increase in non-invasive imaging techniques to screen patients for abnormalities, including cancer (Park et al., 2016). Medical imaging is one of the most basic and common medical diagnostic tools. To trained eyes, they can accurately describe the internal organs of a human being and indicate the presence of pathologies. The first step in many medical image interpretations is image segmentation. The trained eye can segment and analyze the image at the cognitive level. In contrast, computers need specific algorithms for this task (Gal and Stoicu-Tivadar, 2011). Image collection sizes increased dramatically and reached petabytes of data. These volumes cannot be processed on a computer within a reasonable time. Hence contemporary image processing tasks require parallelism (Sozykin and Epanchintsev, 2015).

Developing effective computer vision algorithms for image processing is a challenging task that requires a significant amount of time invested in the prototyping phase (Wang and Hogue, 2020). Visual programming systems aim to facilitate prototyping. We can cite as examples of visual programming systems TOMAAT, CVNodes, Taverna, Kraken, and Khoros-Cantata. TOMAAT is an open-source framework for deployment of complex medical image analysis algorithms in the cloud. It provides a cloud environment for general medical image analysis composed of three basic components: an announcement service, multiple distributed server nodes offering medical image analysis solutions, and client software offering simple user interfaces. TOMAAT requires a Python environment to work (Milletari et al., 2019).

CVNodes is a high-level abstracted interface that leverages the low-level power of OpenCV and thus provides access to general image processing and vision algorithms that are applicable to many domains. CVNodes enables the user to quickly and easily identify problems within each stage of the development pipeline, allowing them to inspect incoming and outgoing data. Its usability, however, still needs to be improved for novice programmers (Wang and Hogue, 2020).

Taverna is a workflow system with OpenCV functions that helps programmers to design and redesign image processing pipelines visually, quickly, and without code. Programmers can graphically control input and output while getting real-time results (Kaewkeeree and Tandayya, 2012). Kraken Image Analysis is a workflow environment software to assist programmers in analyzing image processing algorithms visually and without code. Kraken Image Analysis uses threads for image processing and queues to send data to other threads using shared memory. The system can process workflows faster and requires fewer resources than Taverna (Traisuwan et al., 2015).

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Khoros is a software development environment that includes image processing. Cantata is a visual programming environment built within the Khoros system. In Cantata, each node is an iconic element representing a program. Each directed arc represents a path over which data flows, matching more naturally a mental representation of the problem. By providing a visual environment for problem-solving, Cantata increases the productivity of researchers and application developers, regardless of their programming experience (Young et al., 1995). One of the main problems of the Khoros project is the union of two rather independent paradigms of visual programming: direct development of the graphical user interface and visual programming based on the concept of data flow (Gurevich et al., 2006).

Other systems offer parallel processing to treat large image datasets that demand a long execution time. Programming code to use parallelism is complex, particularly when dealing with data dependencies, memory management, data movement, and processor occupancy (Blattner et al., 2015). Systems that offer parallel processing are VisionGL and Hybrid Task Graph Scheduler (HTGS).

VisionGL is an open-source library that provides a set of accelerated image processing functions, e.g., pixelwise operations, convolution, classical and diffuse mathematical morphology, with dilation, erosion, opening, closing, conditional dilation, and reconstruction (Dantas et al., 2016). VisionGL helps to create image processing operators by automatically generating wrapper code and optimizing image transfers between RAM and GPU (Dantas et al., 2017).

HTGS is a framework and runtime system, which hides data motion, maximizes processor occupancy when running on hybrid computers, and manages memory usage to stay within system limitations. HTGS increases programmer productivity when implementing hybrid workflows that scale to multi-core and multi-GPU systems (Blattner et al., 2015).

On the other hand, workflow systems have become popular tools as they allow the user to develop algorithms as a collection of function blocks, which can be graphically linked to input and output pipelines (Hamidian et al., 2014). Such systems decrease the learning curve for beginning programmers. Systems that use workflow are MATLAB and ImageFlow.

MATLAB is a powerful tool for image processing. Newbies in programming can solve technical problems faster with workflows than programming in traditional languages like C and C++. However, its architecture is very complex and makes learning difficult for beginners (Tong et al., 2011).

ImageFlow enables images to be processed by distributed legacy software coupled with interconnected target systems. ImageFlow's key features are workflow-based image processing, general running service (GRS) for legacy programs, adaptive data transfer engine, and workflow-based software deployment (Cao et al., 2009).

Finally, there are systems that make programming easier and increase productivity through automatic code generation. Examples of systems that generate code automatically are NVIDIA Performance Primitives (NPP), Model-Integrated Computing (MIC), and VisionGL.

The NPP library facilitates the automatic generation of Compute Unified Device Architecture (CUDA) code. While greatly easing the burden, utilizing NPP still requires learning CUDA.

MIC is a graphical environment for designing image processing workflows that automatically generate all the CUDA code, including NPP calls necessary to run the application on a GPU. Users can drag and drop components and connect them to create their workflows. Images are exchanged between consecutive nodes using pointers to avoid unnecessary data transfer. The interpreter automatically analyzes the entire model hierarchy and synthesizes the CUDA code. The execution time with the NPP code is faster than a code implemented sequentially and run on CPU (Li et al., 2012).

VGLGUI is a graphical user interface for image processing that allows visual workflow programming for distributed image processing, using VisionGL functions for automatic wrapper code generation and optimization of image transfers between RAM and GPU (Maciel et al., 2021). This article describes an implementation of the VGLGUI high-level workflow interpreter and compares its processing times running on CPU and GPU with other platforms.

2 VGLGUI WORKFLOW INTERPRETER

As sequential computing becomes limited by the processing speed of silicon, competing approaches, such as parallel and distributed computing, are alternatives for increasingly powerful computing, as is the case with networked systems and GPUs. The design and performance characterization of various competing implementations can be performed primarily on real hardware or by simulating these systems using interpreters and emulators. Each of these alternatives has its respective advantages and disadvantages, with the simulation approach being characterized by po-

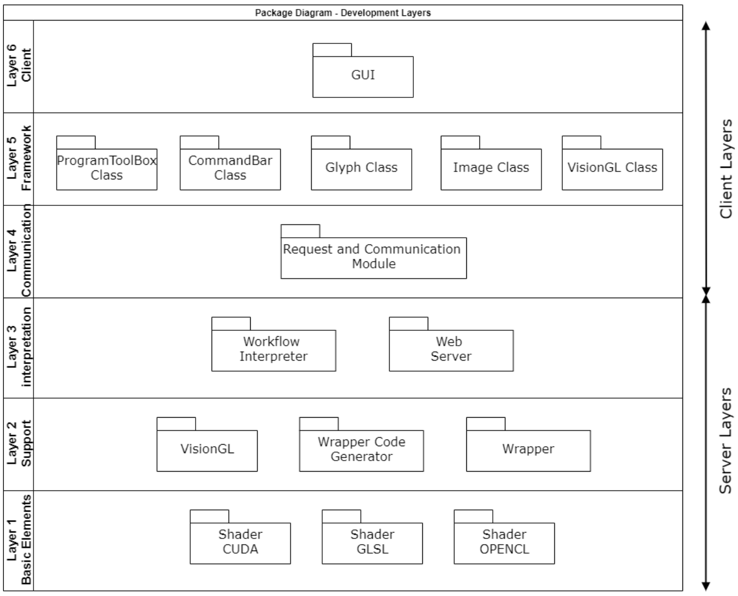


Figure 1: Package diagram: development layers (Maciel et al., 2021).

```
#  Glyph '[GlyphName]'
Glyph:[Library]:[GlyphName]::localhost:[Glyph_ID]:[Glyph_X]:[Glyph_Y]:: -[var_str] '[var_str_value]'
Glyph:[Library]:[GlyphName]::localhost:[Glyph_ID]:[Glyph_X]:[Glyph_Y]:: -[var_num] [var_num_value]

#  Connections '[GlyphName]'
NodeConnection:data:[output_Glyph_ID]:[output_varname]:[input_Glyph_ID]:[input_varname]
```

Listing 1: Workflow file format.

tentially improved versatility in changing configurations at the expense of longer runtimes (da F. Costa, 2020).

An interpreter is a program that analyzes source code in real-time without compiling it first. The elements of an interpreter are the lexer, which transforms a simple text string into a sequence of tokens; the parser, which takes a sequence of tokens and produces an abstract syntax tree (AST) of a language; and the evaluator, which is a program that executes the AST (Sakib Hadžiavdić, 2020).

VGLGUI provides functionalities to create, edit, execute and stop the execution of workflow files through glyphs. A glyph is an iconic representation of a function connected to others, forming a data processing stream. Each glyph represents a VisionGL function. Figure 1 shows the six layers of VGLGUI. Each layer provides a strict and well-defined interface with the layers above it. The workflow interpreter is contained in layer 3, Interpretation (Maciel et al., 2021).

A workflow consists of an orchestrated flow of data processing components. A workflow can be described as a sequence of work operations that can be simple or complex (Traisuwan et al., 2015). Workflow means that work is done by different components in a fixed sequence (Tong et al., 2011).

The workflow interpreter of the VGLGUI interface has an architecture based on glyphs and connections. The relationship between them is governed by the rules below.

1. A glyph corresponds to a graph vertex and represents a function from the VisionGL library.
2. An edge is a connection between glyphs and represents the image to be processed.
3. Each connection has an image stored.
4. A source-type glyph loads or creates an image and has only output connections.
5. A sink-type glyph shows or saves an image and has only input connections.
6. Glyphs have a READY status that informs if it is ready to execute and a DONE status that informs if it has already been executed. Both statuses start as FALSE.
7. Connections whose input glyphs have already been executed, therefore having their correspond-

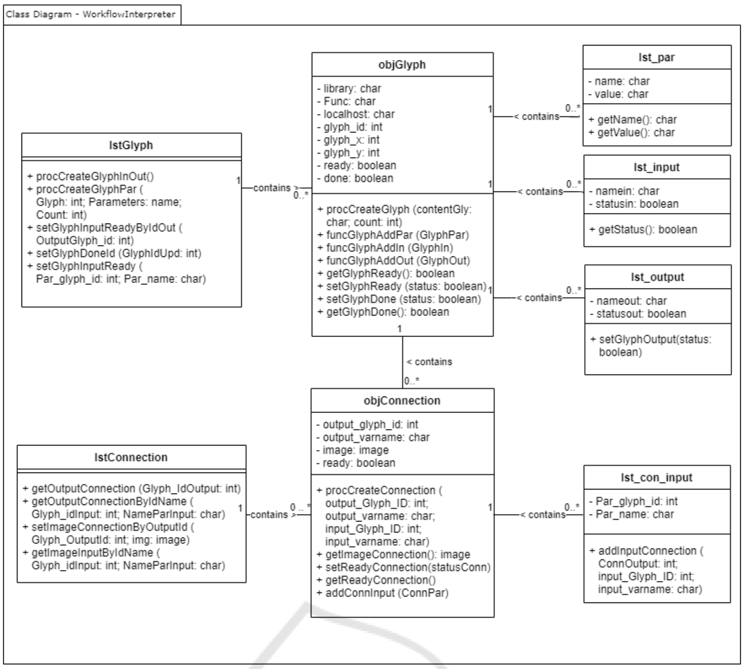


Figure 2: Class diagram: workflow interpreter.

ing images generated, have status READY = TRUE, which means that the image is ready to be processed.

8. Glyphs may have a list of input connections. When all connections have status READY = TRUE, the glyph changes its status to READY = TRUE.
9. Source-type glyphs are created with status READY = TRUE.
10. Glyphs whose status is READY = TRUE are executed.
11. Glyph status becomes DONE = TRUE after its execution.

Listing 1 shows the two types of command lines used to create glyphs and connections based on the Khoros workflow file format.

The programmer uses VGLGUI to develop his image processing pipeline, and the interface generates the corresponding workflow file on disk with the extension `wksp`.

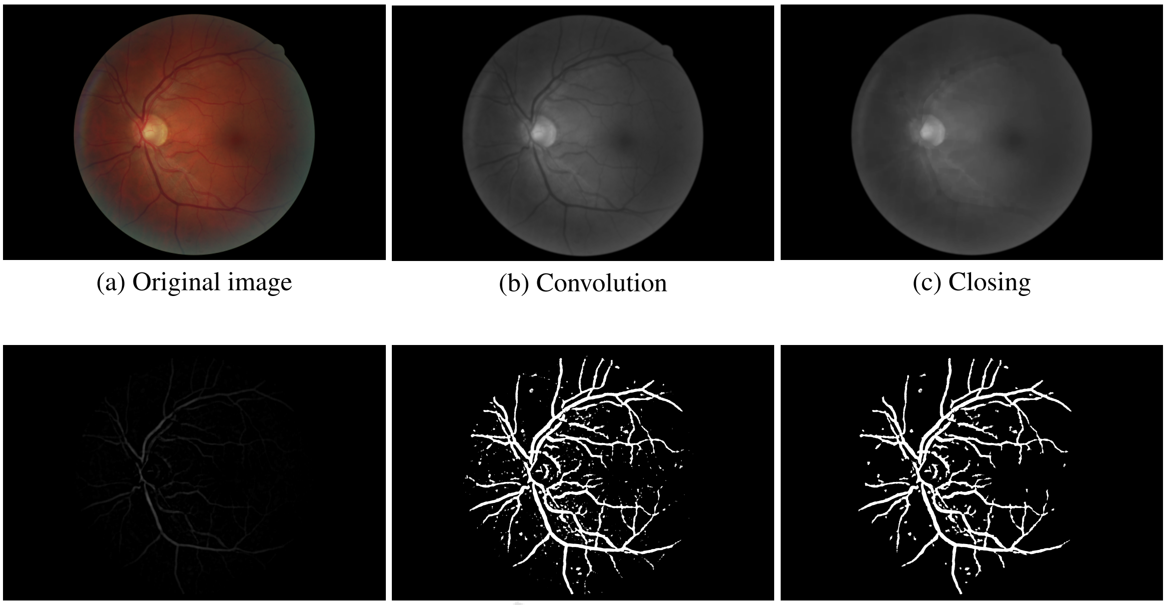
To edit the image processing workflow in VGLGUI, the user chooses the *File - Open workflow file* option from the menu, indicates the file path, and clicks on the *Open* button. The VGLGUI Interpreter reads the glyph-type command lines, identifies the information about the glyph—screen position, function to execute, and execution parameters—and creates the graphical representation of the glyph in the VGLGUI Workspace. Then, the interpreter reads the connection-type command lines and draws the graphical representation of the connections in the VGLGUI Workspace.

Each glyph input is linked to a single glyph output, its immediate predecessor in the image processing sequence. On the other hand, each glyph output can be connected to more than one glyph input.

The VGLGUI Interpreter generates an AST and stores the information of the glyphs and their connections in memory, Figure 2 shows the classes used in the internal representation of workflows in memory. The VGLGUI Interpreter was developed in Python. The user edits the workflow graphically, and when clicking on the menu *File - Save workflow file*, the changes are saved to disk. Error handling is performed during the reading and execution of the workflow file to avoid basic program failures. Error messages show the workflow line with the error and the rule not met.

3 RESULTS

This study demonstrates the usage of two sample workflows with VGLGUI: Demo and Fundus. Demo workflow shows the basic usage of the interpreter. Fundus workflow shows a real-life scenario by segmenting a retinography image. For the sake of comparison, both workflows were tested with the same sample image from the HRF dataset (Budai et al.,



(a) Original image (b) Convolution (c) Closing

(d) Subtraction (e) Threshold (f) Reconstruction

Figure 3: Results of the Fundus image processing workflow.

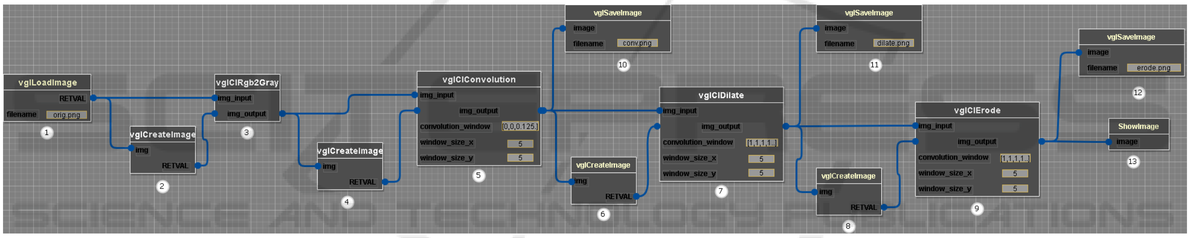


Figure 4: Visual representation of the Demo workflow.

2013a; Budai et al., 2013b). Figure 3 shows the resulting images of the Fundus image processing workflow. Both workflows were run on a desktop computer with a CPU Intel Core i3-4130 3.40GHz with 12GB RAM and a GPU NVIDIA GeForce GTX 1070 with 8GB RAM. The workflows used basic operations such as image load, image save, convolution, and mathematical morphology operations, such as dilation and erosion. The Fundus workflow also uses subtraction, closing, and reconstruction operations.

The interpreter was tested with both workflows running on the CPU and GPU. Both workflows were also ported to Python with OpenCV running on the CPU; and C++ with VisionGL running on the GPU.

3.1 Demo Workfow

The Demo workflow aims to demonstrate is to demonstrate the usage of basic functions such as convolution, dilation, and erosion. Figure 4 is the visual representation of the Demo workflow.

Glyph 1 loads the image to be processed. Glyph 2 allocates an image with the same size as the input image required by `vglClRgb2Gray`. Glyph 3 applies the `vglClRgb2Gray` function to convert the input image to grayscale. The VisionGL function `vglClConvolution` applies a Gaussian blur to reduce noise. Glyph 10 saves the result of the convolution to a file. Glyph 7 applies the `vglCLDilate` function to increase the bright areas. Glyph 8 allocates an image of the same size as the input image required by `vglClErode`. Glyph 12 saves the result of the erosion to a file. Glyph 9 executes the `vglClErode` to eliminate bright areas smaller than the structuring element. Glyph 13 shows the resulting final image on the screen.

Table 1 shows the execution times of the Demo image processing workflow in milliseconds.

3.2 Fundus Workflow

In the Fundus workflow, the objective is the application of a pipeline for blood vessel segmentation in retinal images (Dantas et al., 2017). The general steps of the pipeline are convolution (Gaussian blur), closing and subtraction (black-hat), thresholding, and opening by reconstruction. The filters and structuring elements were separated into a column filter and a line filter. The results are identical, but the time complexity is much lower.

Figure 3 shows the resulting images from the Fundus image processing workflow. Table 2 shows the processing times in milliseconds.

3.3 Discussion

The workflow interpreter, whose structure was detailed in this study, is a layer of the VGLGUI architecture that links the VisionGL functions and the graphical interface to facilitate the learning of image processing pipeline programming. VGLGUI uses OpenCL to parallelize processing on the GPU.

In VGLGUI, the developer elaborates his image processing pipeline without coding. The functions are chosen from a menu generated from the functions available in VisionGL. If necessary, the user can create his own functions in OpenCL, and the library will automatically generate its wrapper functions and menu entries. These features improve the learning curve of novice programmers and accelerate development.

Two workflows were created to demonstrate how the interpreter works. Demo workflow demonstrates the usage of basic functions. Fundus workflow demonstrates the usage in a real-life scenario by segmenting a retinography image. Both workflows were tested with an image with about 18 megapixels. Both workflows were ported to Python and C++, and the runtimes were obtained.

The average processing time of the Demo workflow by the interpreter running on the GPU was 62.65 ms and by the Python version running on the CPU was 437.07 ms. Thus the interpreter can run a simple workflow a few times faster than Python. GPU occupancy was low in this workflow, meaning that the Python calls done by the interpreter and that run on the CPU cause a bottleneck when GPU operations are too fast.

On the other hand, the interpreter's average processing time by the Fundus workflow on the GPU was 916.05 ms, while the Python version on the CPU was more than 1300000 ms. Fundus workflow runs on the GPU hundreds of times faster than its Python version.

Table 1: Demo workflow runtime, in milliseconds, on an image with 5184×3456 pixels.

Operations	Python CPU	Interpreter CPU	Interpreter GPU	VisionGL GPU
Rgb2Gray	7.46	342.18	1.35	1.36
Convolution 51×51	357.72	18119.85	21.36	20.38
Dilation 51×51	35.06	19659.90	19.95	18.78
Erosion 51×51	36.83	20294.23	19.99	18.80
TOTAL	437.07	58416.16	62.65	59.32

Table 2: Fundus workflow runtime, in milliseconds, on an image with 5184×3456 pixels.

Operations	Python CPU	Interpreter CPU	Interpreter GPU	VisionGL GPU
Rgb2Gray	5.42	301.89	1.39	1.33
Convolution 51×51	358.66	17861.99	22.07	20.55
Closing 51×51	64.06	38960.01	40.87	38.76
Subtraction	4.22	475.56	1.03	1.03
Threshold	36.49	475.56	1.03	0.71
Reconstruction 17×17	1321649.79	1301049.64	849.61	1002.88
TOTAL	1428427.05	1359124.65	916.05	1065.26

As the reconstruction takes a long time to complete, GPU occupancy is higher, and the CPU bottleneck impairs less the processing speed. Frequent transfers of data between the RAM and the GPU memory also may cause a bottleneck. As the image is transferred only once from the RAM to the GPU memory and there remains during the whole workflow processing, there is no latency associated with that.

The runtimes of the workflows implemented in C++ with VisionGL running on the GPU were similar to the runtimes of the workflows processed by the interpreter running also on the GPU.

4 CONCLUSIONS

This study proposes a workflow interpreter to facilitate the implementation of image processing workflows that support parallelization by using OpenCL.

The speedup varies between one to three orders of magnitude compared to a Python version using OpenCV and running on the CPU. Part of this variation may be due to the CPU bottleneck, which is relatively narrower when the functions that run in the GPU are too fast. When the operations that run in the GPU are more demanding, e.g., composed of many window operations such as the reconstruction, GPU occupancy increases, and the speedup is bigger.

The proposed system also can facilitate the implementation of image processing pipelines by providing a visual workflow editor. Visual programming may be easier and more intuitive to use than standard programming languages and may also accelerate the development by providing a ready-to-use testbed for image processing experiments.

Future versions of VGLGUI may include new image processing functions, either by augmenting VisionGL or exposing image processing functions from OpenCV. We are also considering the implementation of a scheduler to distribute the load across servers.

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