

Brain Image Registration Analysis Workflow for fMRI Studies on Global Grids

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Abstract

Scientific applications like neuroscience data analysis are usually compute and data-intensive. With the use of the additional capacity offered by distributed resources and suitable middlewares, we can achieve much shorter execution time, distribute compute and storage load, and add greater flexibility to the execution of these scientific applications than we could ever achieve in a single compute resource.

In this paper, we present the processing of Image Registration (IR) for Functional Magnetic Resonance Imaging (fMRI) studies on Global Grids. We characterize the application, list its requirements and then transform it to a workflow. We then execute the application on Grid'5000 platform and present extensive performance results. We show that the IR application can have 1) significantly improved makespan, 2) distribution of compute and storage load among resources used, and 3) flexibility when executing multiple times on the Grid with the use of suitable middlewares.

1 Introduction

Nowadays many scientific experiments such as climate modeling, structural biology and chemistry, neuroscience data analysis, and disaster recovery are conducted through complex and distributed scientific computations that are represented and structured as scientific workflows [12]. Scientific workflows usually need to process a huge amount of

data and are computationally intensive activities. Neuroscience data analysis is one such application that has been a focus of much research in recent years (NIFTI, BIRN) (see §2).

The neuroscience data analysis application we present in this paper has several tasks that need to be structured according to their data dependencies for correct execution. Both the data and computation requirements are very high. Given the typically large number of subjects' data being analyzed, it takes significant amount of time for this application to produce results when executed as a sequential process on limited resources. Moreover, scientists may need to re-run the application by varying run-time parameters. Often researchers and users around the globe may share the results produced. To facilitate these requirements the application may leverage the power of distributed resources presented by platforms such as Grids. By executing this application on distributed resources execution time can be minimized, repeated executions can be performed with little overhead, reliability of execution can be increased, and resource usage can be distributed. It is a very demanding task for researchers to handle these complex applications directly on Global Grids without proper management systems, interfaces, and utilities.

A scientific workflow management system is one of the popular approaches that provide an environment for managing scientific experiments, which have data dependent tasks, by hiding the orchestration and integration details inherent while executing workflows on distributed resources.

The Gridbus Workflow Engine (GWFE) [21], is one

such Grid-based workflow management system that aids users (scientists) by enabling their applications to be represented as a workflow and then executed on the Grid from a higher level of abstraction. The GWFE provides an easy-to-use workflow editor for application composition, an XML-based workflow language for structured representation, and a user-friendly portal with discovery, monitoring, and scheduling components that enables users to select resources, upload files and keep track of the application's progress.

In this paper, we present Image Registration (IR) for Functional Magnetic Resonance Imaging (fMRI) studies. We first characterize the application and identify its requirements. We then execute this application on Global Grids with the help of GWFE and present detailed analysis of the results. Our performance results and technology used could directly assist neuroscientists using brain imaging technology in clinical areas such as epilepsy, stroke, brain trauma and mental health.

The rest of the paper is structured as follows: Section 2 presents related work, Section 2 describes the workflow application scenario, its components, and requirements. In Section 4 we describe the workflow execution life cycle and the major components that users can use to interact with the system. Section 5 presents an experimental evaluation of a real biomedical application by executing it on the Grid. Section 6 concludes the paper and discusses some future work.

2 Related Work

Several projects are investigating workflow technology with respect to our target application and Global Grid scheduling. These related works are categorized as **application** and **Workflow Management Systems** and described below.

Application: Olbarriaga et al. [14] present the Virtual Laboratory for fMRI (VL-fMRI) project, whose goal is to provide an IT infrastructure to facilitate management, analysis, and sharing of data in neuroimaging research with a focus on functional MRI. We share a common objective to facilitate the data logistics and management in fMRI analysis via workflow automation. Their system could use our workflow management system as a pluggable component.

Neurobase [9] uses grid technology for the integration and sharing of heterogeneous sources of information in neuroimaging from both data and computing aspects.

Buyya et al. [3] studied instrumentation and distribution analysis of brain activity data on global grids. They present the design and development of Magnetoencephalography (MEG) data analysis system. They describe the composition of the neuroscience application as parameter-sweep application and its on-demand deployment on Global Grids.

Ellis et al. [8] executed their IR algorithm by registering

several couples of T1 MRI images coming from different subjects in 5 minutes on a Grid consisting of 15 2GHz Pentium IV PCs linked through a 1Gigabit/s network.

The LONI Pipeline [16] was developed to facilitate ease of workflow construction, validation and execution like many similar workflow environments, primarily used in the context of neuroimaging.

The NIMH Neuroimaging Informatics Technology Initiative (NIFTI¹) was formed to aid in the development and enhancement of informatics tools for neuroimaging. Likewise, the Biomedical Informatics Research Network (BIRN²) is another high profile effort working to develop standards (eg. LONI) among its consortia membership.

Workflow Management Systems: Deelman et al. [6] have done considerable work on planning, mapping and data-reuse in the area of workflow scheduling. They propose Pegasus [7], which is a framework that maps complex scientific workflows onto distributed resources such as the Grid. DAGMan, together with Pegasus, schedules tasks to Condor system. With the integration of Chimera [10] and Pegasus based [6] mapping, it can execute complex workflows based on pre-planning. The Taverna project [13] has developed a tool for the composition and enactment of bioinformatics workflows for the life science community. This tool provides a graphical user interface for the composition of workflows. Other well-known projects on workflow systems include GridFlow [4], Unicore [17], ICENI [11], GridAnt [2] and Triana [19].

3 Scientific Workflow Applications: A Scenario and Requirements

We describe the Image Registration (IR) procedure for fMRI as a Scientific Workflow Application. We construct the IR workflow and describe each of its tasks, and then tabulate the requirements of executing each task in the workflow.

fMRI and IR: fMRI attempts to determine which parts of the brain are active in response to some given stimulus. For instance, a person (referred as subject), in the Magnetic Resonance (MR) scanner, would be asked to perform some task, e.g., finger-tap at regular intervals. As the subject performs the task, researchers effectively take 3-D MR images of his brain. The goal is to identify those parts of the brain responsible for processing the information the stimulus provides.

IR is ubiquitous in fMRI analysis, especially in the case of multi-subject studies. IR is the process of estimating an optimal transformation between two images, also known as "Spatial Normalization" in functional neuroimaging [15]. When registering images we are determining a geometric

¹<http://nifti.nimh.nih.gov>

²<http://nbhirm.net>

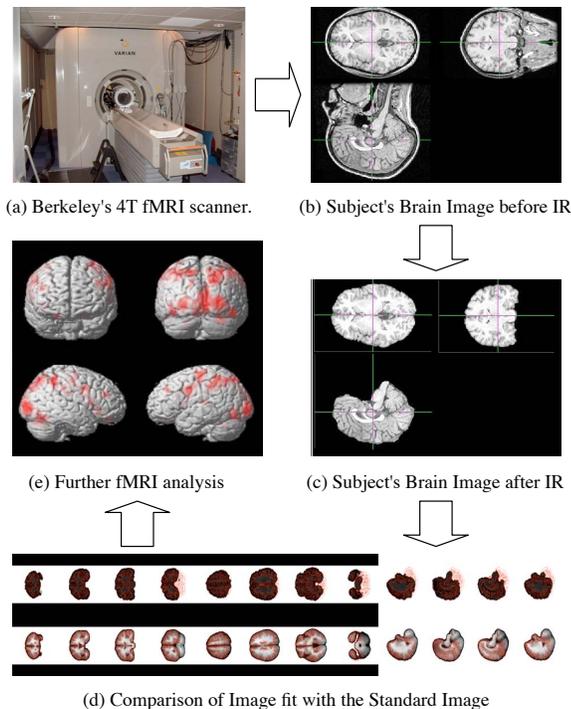


Figure 1: Image Registration and fMRI.

transformation, which aligns one image to fit another. The aim is to establish a one-to-one continuous correspondence between the brain images of different individuals. The transformation will reduce the anatomical variability between high-resolution anatomical brain images from different subjects. This enables analysts to compute a single activation map representing the entire group of subjects or to compare the brain activation between two different groups of subjects.

The IR procedure and its relation to fMRI is depicted in Figure 1. The scanner acquires high-resolution images of each subject's brain. Due to subject movement the images can be oriented in different positions at the time of scanning. One such image of a subject before registration is shown in Figure 1 (b). The registration process ensures that all the images of different subjects are normalized against a standard image and in a common 3D space. The normalized image of the subject is shown in Figure 1 (c). After normalization, the subject's normalized image is compared with the *atlas* (reference image) for the quality of fit. This comparison is shown in Figure 1 (d). The workflow we study in this paper, first produces the *atlas*, then produces the comparison image (Figure 1 (d)) as output for each subject.

Application Description: The IR procedure, expressed as a scientific workflow is shown in Figure 2. The tasks are linked according to their data dependencies. Individual tasks that form the workflow are described below [18] [1].

BET: (Brain Extraction Tool) deletes non-brain tissue from an image of the whole head.

FSLMATHS: allows mathematical manipulation of images.

MAKEAHEADER: generates a header (.hdr) file based on the parameters (type, x-y-z dimensions and size).

ALIGNLINEAR: is a general linear intra modality registration tool. It generates .air files that can be used to reslice the specified reslice data set to match the specified standard data set. We use affine 12-parameter model.

DEFINECOMMONAIR: defines new .air files with a new standard file that defines the "average" position, size and shape of the various reslice files.

RESLICE: takes a .air file and uses the information that it contains to load the corresponding image file and generate a new, realigned file.

SOFTMEAN: averages together a series of files.

ALIGN_WARP: is a nonlinear registration tool that generates a .warp file that can be used to reslice the specified reslice data set to match the specified standard data set.

RESLICE_WARP: takes a .warp file and uses the information that it contains to load the corresponding image file and generate a new, realigned file.

FLIRT: performs affine registration. It produces an output volume, where the transform is applied to the input volume to align it with the reference volume (*atlas* created in previous steps).

SLICER: takes 3D image and produces 2D pictures of slices.

PNGAPPEND: processes addition/subtraction of .png images.

Application Requirements: According to Zhao et.al [22], in a typical year the Dartmouth Brain Imaging Center about 60 researchers pre-process and analyze data from about 20 concurrent studies. The raw fMRI data for a typical study would consist of three subject groups with 20 subjects per group, five experimental runs per subject, and 300 volume images per run, yielding 90,000 volumes and over 60 GB of data. Intensive analysis begins once the images are processed. IR forms a part of the image pre-processing step using only the high-resolution data, which represents a minor portion of the entire workflow's execution time.

Table 1 lists each task, its input files and sizes, its average computation time (\bar{w}_i) on a single machine, and standard deviation (σ) computed over 40 subjects on a set of 10 random machines in Grid'5000 [5].

A complete execution of the workflow of 40 subjects on a single CPU with single core (without local load) takes two and a half days to complete. The total storage space needed

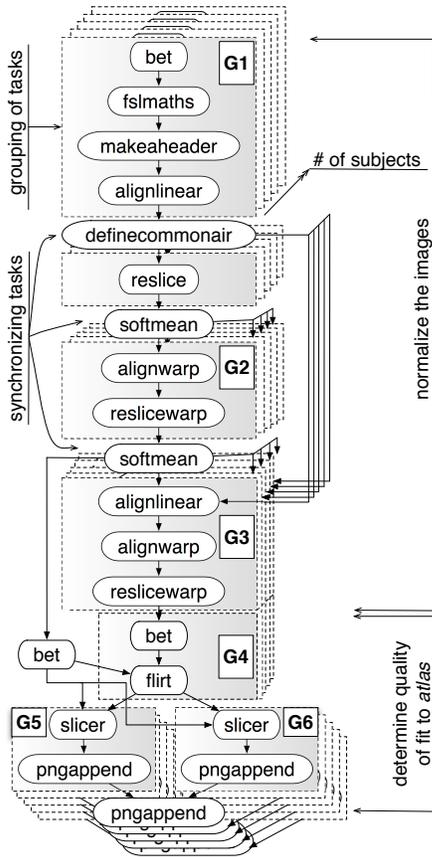


Figure 2: Image Registration Workflow.

for the complete execution of 40 subjects exceeds 20GB on a single machine when the intermediate files are retained. Moreover, the computation time and storage requirements limit the number of subjects that can be used for execution at one time on a single machine.

When the application is executed on distributed resources with no resource scarcity the application should take as much time to execute all the subjects as a single machine would take to execute a single subject workflow without local load. However, the real execution time is higher than the ideal case (~ 69 minutes) for 1 subject as shown in Table 1, due to the significant amount of time taken to transfer the intermediate files from one resource to another. We can decrease the transfer time by allowing multiple tasks to run on a single machine (grouping of tasks). Also, the synchronizing tasks take longer to execute when there are more subjects. The coordination time taken by the middleware also adds to the overall increase in total execution time.

4 Workflow Management on the Grid

The life cycle of deployment of the workflow is depicted in Figure 3. In the collection phase, scientists provide the input data, batch scripts, sample output files, and application requirements. In order to run the application on the Grid with heterogeneous resources the executables are

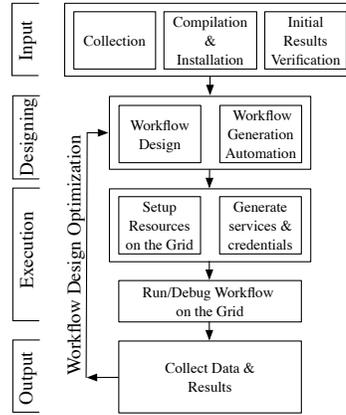


Figure 3: Deployment Cycle.

required to be compiled and installed (can be submitted at runtime) at both remote and local sites for quality assurance or *initial results verification*. This step involves the testing of conformance of our execution with that of the sample results provided by the scientists. Once the initial results are verified the workflow structure and its details need to be designed. The generation of the workflow in terms of the workflow language used needs to be automated by taking into account the run-time parameters that users might want to change.

In the *Execution* phase the resources where the application can be executed need to be setup. The resource list, its credentials and the services provided by each resource need to be inserted into the catalogue. With changing resource availability and conditions the services and credentials are required to be generated for each execution with the help of the catalogue. The application is then executed on the Grid. Usually debugging and testing is done while the application is being executed, but this depends on the software development process being used. Depending on the analysis of the results from the output phase, the workflow design can be further optimized according to the requirements of the user.

Users interact with the Gridbus Workflow Engine system through the Grid Portal. We describe the following key components that provide users access to the scientific application.

Grid Portal: The primary user interface for our IR application is a Web Portal that encompasses the following functionalities:

1. A workflow editor, which enables users to compose new workflows and modify existing ones.
2. A submission page, through which users can upload to the system, all necessary input files to run a workflow including the workflow description file, credentials, and services files (Figure 4 (b)).
3. A monitoring and output visualization page, which allows users to monitor multiple workflow executions in progress. The most common monitoring activity con-

Table 1: Characteristics of tasks for a single subject.

note: X = hires, '-' = not applicable (depends on # of subjects), taskname(*) = same task but different execution instance, N = subject index ($N \in \mathbb{Z}$)

#	Task Name	Input Files	Source Tasks	Size of i/p (MB)	\bar{w}_i (sec)	σ
1	bet(1)	X.{hdr,img}	Staging server	16	45	11.91
2	fslmaths	bX.{hdr,img}	bet(1)	16	1	0.42
3	makeaheader	bX.{hdr,img}	fslmaths	16	$\ll 1$	-
4	alignlinear(1)	bX.{hdr,img}	fslmaths	16	2	0.47
5	definecommonair	X.air, bX.{hdr,img}	alignlinear(1)	16	94	-
6	reslice	X.air.aircommon, bX.{hdr,img}	definecommonair	16	5	0.5
7	softmean(1)	X-reslice.{hdr,img}	reslice	20	140	-
8	alignwarp(1)	atlas-linear.{hdr,img}, X-reslice.{hdr,img}	softmean(1)	40	971	620.17
9	reslicewarp(1)	atlas-linear.{hdr,img}, X-reslice.{hdr,img,warp}	alignwarp(1)	40	9	1.88
10	softmean(2)	X-reslice-warp.{hdr,img}	reslicewarp(1)	20	111	-
11	bet(2)	atlas.{hdr,img}	softmean(2)	20	11	1.5
12	alignlinear(2)	bX.{hdr,img}, atlas.{hdr,img}	definecommonair, softmean(2)	36	23	10.25
13	alignwarp(2)	X.air, atlas.{hdr,img}, bX.{hdr,img}	alignlinear(2)	36	2656	1501
14	reslicewarp(2)	bX.{hdr,img,warp}	alignwarp(2)	16	9	1.88
15	bet(3)	nX.{hdr,img}	reslicewarp(2)	16	15	1.3
16	flirt	batlas.{hdr,img}, nbX.{hdr,img}	bet(2), bet(3)	56	6	0.44
17	slicer(1)	batlas.{hdr,img}, N-fit.{hdr,img}	bet(2), flirt	80	8	0.44
18	pngappend(1)	{sla,slb,...,slk,sl1}.png	slicer(1)	0.3	4	0.51
19	slicer(2)	batlas.{hdr,img}, N-fit.{hdr,img}	bet(2), flirt	80	8	0.44
20	pngappend(2)	{sla,slb,...,slk,sl1}.png	slicer(2)	0.3	4	0.28
21	pngappend(3)	{N-fit1, N-fit2}.png	pngappend(1),pngappend(2)	0.8	4	0.28
22	OUTPUT	N-fit.png	pngappend(3)	(o/p size) 0.8		
Average data volume and computation time required for a single subject registration:				558.2 MB	~ 69 min	

sists of keeping track the status of each task through the workflow monitor, which provides a real-time updated graphical representation of workflow tasks. The application's output is presented in the form of images (Figure 4 (d), 1 (d)).

4. A resource information page, which shows the characteristics of all available grid resources.
5. An application specific page, which in the current implementation provides generation of IR workflow description files by taking the number of subjects as input.

Although the current incarnation of this Grid Portal is targeted at an IR application, our design is in no means limited to such application. Apart from few parts of the output visualization page and the application specific page, the portal infrastructure is generic enough to allow the porting of almost any workflow application into the portal. We now describe in more detail the Workflow Editor, the Workflow Monitor, and the Workflow Engine.

Workflow Editor: The Gridbus workflow editor provides a Graphical User Interface (GUI) that enables users to create and modify existing workflows. The definition of the workflow is based on an XML-based workflow language (xWFL). Using the editor users design and create the workflows for complex scientific procedures by dragging and dropping boxes and arrows, connecting them, and defining their properties (input, output, parameters etc.). Boxes and directed arrows represent workflow tasks and data dependencies between them, respectively.

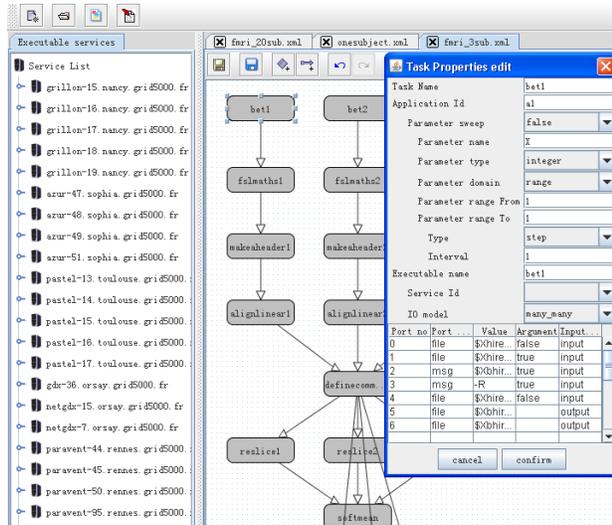
The GUI isolates users from the complexity of composing and editing XML entries in the files. However, for advance users, editor provides direct access to the XML details of the workflow design. As the workflow editor can be accessed through the workflow portal, users can create or

edit and save the workflows both locally and on the server. Common editing operations such as cut, copy, paste can be concurrently performed on multiple workflows.

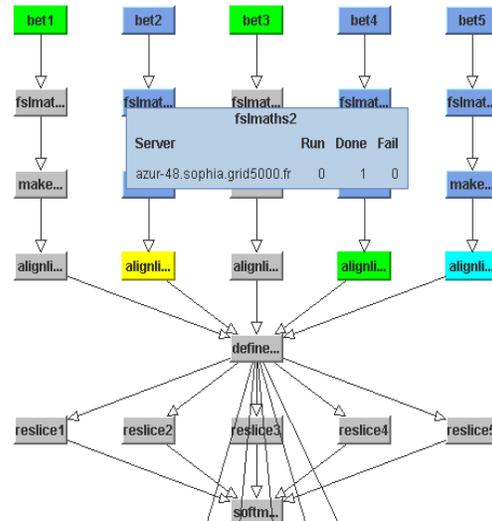
Workflow Monitor: The Gridbus Workflow Monitor provides a GUI for viewing the status of each task in the workflow. Users can easily view the ready, executing, stage-in, and completed tasks as depicted in Figure 4. Task status is represented using different colors. Users can also view the site of execution of each task, the number of tasks being executed (in case of a parameter sweep type of application) and the failures for each task, if any. The workflow structure is editable such that users can drag tasks and separate tasks of interest when there are numerous tasks in the workflow.

Gridbus Workflow Engine: Scientific application portals submit the task definitions along with their dependencies in the form of the workflow language to GWFE. Then the GWFE schedules the tasks in the workflow application through Grid middleware services and manages the execution of tasks on the Grid resources. The key components of GWFE are: workflow submission, workflow language parser, resource discovery, dispatcher, data movement and workflow scheduler.

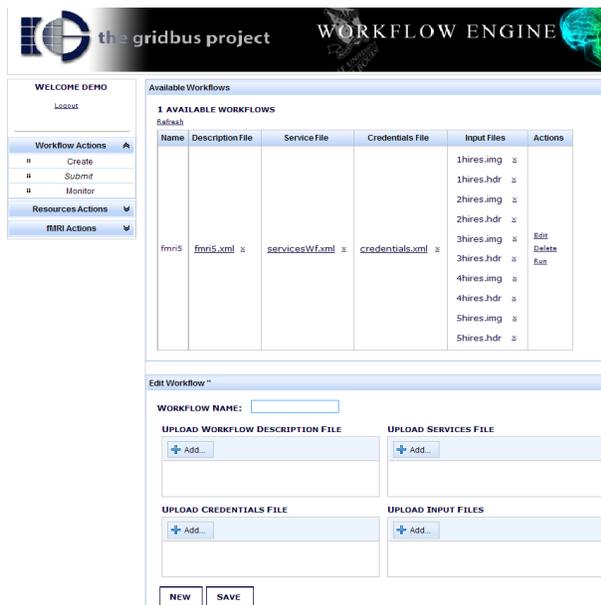
GWFE is designed to support an XML-based WorkFlow Language (xWFL). This facilitates user level planning at the submission time. The workflow language parser converts workflow description from XML format to Tasks, Parameters, Data Constraint (workflow dependency), Conditions, etc., that can be accessed by workflow scheduler. The resource discovery component of GWFE can query Grid Information Services such as Globus MDS, directory service, and replica catalogues, to locate suitable resources for execution of the tasks in the workflow by coordinating with middleware technologies such as Gridbus Broker



(a)



(c)



(b)

Workflow Executions for user demo

4 AVAILABLE WORKFLOW EXECUTIONS

Refresh

ID	Workflow Name	Actions
4547b63f-a929-489b-act6-88ea36d3e843	fmr15	Show output files Show tables Show monitor Delete
bb335b63-f938-4fb4-8b32-333a550a06df	fmr20	Show output files Show tables Show monitor Delete
c49c1d99-6b64-4e05-907c-bb0352b24769	fmr15	Show output files Show tables Show monitor Delete
bf34e92a-7277-40ef-9ed7-58d06858d4b1	fmr15	Show output files Show tables Show monitor Delete



(d)

Figure 4: Grid Portal. (a) Workflow editor. (b) The submission interface. (c) Workflow monitor showing status of tasks in colors (cyan = ready, yellow = submitting, green = executing, blue = done). (d) Multiple workflow runs and output.

[20]. GWFE uses Gridbus Broker for deploying and managing task execution on various middlewares as a dispatcher component. Using the Gridbus Broker as the middleware mediates access to distributed resources by (a) discovering resources, (b) deploying and monitoring task execution on selected resources, (c) accessing data from local or remote data source during task execution, and (d) collating and presenting results.

GWFE is designed to be loosely-coupled and flexible using a tuple spaces model, event-driven mechanism, and subscription/notification approach in the workflow scheduler, which is managed by the workflow coordinator com-

ponent. The data movement component of GWFE enables data transfers between Grid resources by using SFTP and GridFTP protocols. The workflow executor is the central component in GWFE. With the help from dispatcher component it interacts with the resource discovery component to find suitable Grid resources at run time, submits a task to resources, and controls input data transfer between task execution nodes. In addition to random and round-robin scheduling policies, GWFE also has a Just-In-Time scheduling policy that allows the resource allocation decision to be made at the time of task submission in order to better adapt to the changing dynamic Grid environment.

5 Experimental Evaluation

The IR application together with GWFE was demonstrated at the First IEEE International Scalable Computing Challenge (SCALE 2008) in conjunction with CCGrid 2008, May 19-22, 2008, using resources provided by SUNY at Binghamton and the University of Melbourne. For this paper we executed the application on Grid'5000 [5].

We now describe the experiment setup, results, and observations.

5.1 Experiment Setup

We executed the IR workflow with 40, 20, 10, and 2 subjects. By varying the number of subjects used we calculated the makespan of the workflow, total storage space required for execution, and parallelism that can be achieved. We grouped the tasks when there was more than a single sequential task between two synchronizing tasks, as depicted in Figure 2. Grouping tasks implicitly demands more than one task to be executed at the same site where it is submitted, unlike the ungrouped version where all tasks would be distributed.

We used the resources provided by Grid'5000. The Grid'5000 project provides a highly reconfigurable, controllable, and monitorable experimental Grid platform gathering 9 sites geographically distributed in France featuring a total of 5000 processors [5]. Table 2 lists the Grid'5000 sites used for the experiment. The resources were reserved for the duration of the experiment. The reservation ensured that the Grid resources were dedicated to our experiment. We used resources with the 'x86_64' CPU architecture with AMD Opteron Processors-246, 248, 250, 252, and 275. We used 8 out of the 9 sites (excluding Grenoble). The distributed resources across 8 sites have varying network interconnection bandwidth, number of cores per CPU, CPU frequency, memory, and storage space available [5].

As a measure of performance, we used average makespan as the primary metric. Makespan of each workflow is measured by taking the difference between the submission time of the first submitted task and the output arrival time of the last exit task to be executed on the system. This time includes the staging-in of the input files to the entry tasks and the staging-out of the results from the exit tasks.

5.2 Results and Observations

Table 2 lists the number of cores used at each site, the number of tasks submitted to the site and the average computation time used at the site for each experiment group. Figure 5 depicts the total makespan for different subjects, comparison of makespan between grouped and ungrouped tasks of the workflow, size of data produced during the execution, and parallelism of tasks executed in time by the GWFE.

Execution of the IR workflow on the Grid showed significant advantages over a single machine. The total makespan of the workflow decreased considerably from 2.5 days in a single machine to approximately 3 hours on the Grid. The storage requirements were distributed among the resources used. As the number of subjects used was increased, the makespan increased slightly. This can be attributed to the increase in execution time of synchronizing tasks and the coordination time required by the system for additional tasks. The main point to be noted is that as the number of subjects was increased, the average makespan remained within similar bounds and did not increase exponentially, as can be seen for 40, 20, and 10 subjects in Figure 5 (a). By inference for more than 40 subjects the makespan should not increase by more than double the difference between the 40 subject and 20 subject makespan.

Grouping of tasks reduced the transmission of data between individual tasks as they were executed on the same machine the group was submitted to. Also, no coordination was required for the individual tasks in the group. This contributed to the reduced makespan in the case of grouped tasks. Figure 5(b) shows that the grouping of tasks that have higher value of standard deviation of execution did not yield an optimized makespan. Ungrouping tasks with higher execution time and a higher standard deviation value gave lower makespan than the grouped version (center of the graph) of that set of tasks. Tasks with lower execution time and lower standard deviation value had lower makespan value when grouped than when ungrouped.

The size of data produced during the execution of the workflow increased when the number of subjects was increased. The input data size (16MB per subject) was low in comparison to the total data produced during the execution as shown in Figure 5(c).

Due to the use of highly available resources, almost all the workflow's ready tasks were executed in parallel, as depicted in Figure 5(d). The graph shows the plot of tasks that finished execution versus time. At a certain interval in the beginning of execution most of the tasks finished execution at the same time showing the parallelism of execution of tasks. Most of the grouped tasks finished execution at the beginning of the execution interval unlike ungrouped tasks. This early execution behaviour helped reduce the makespan of the whole workflow as the grouped tasks executed more than one task at a time through a bash script, which is seen as a single task by the resource. In the case of ungrouped tasks each task needed to be mapped onto a resource and as the resource approached its maximum job limit, no more tasks could be submitted to it. This is also the reason that fewer grouped tasks were executed on the system than ungrouped tasks after 100 seconds.

We used a Just-In-Time scheduling algorithm to schedule the tasks. As the tasks became ready the scheduler was

Table 2: Grid5000 sites used; # cores, # tasks executed and average computation time (\bar{c}) taken on each site for each experimental group.

Name	10Sub			10Sub (G)			20Sub			20Sub (G)			40Sub			40Sub (G)			
	#Cores	#Tasks	\bar{c} (sec)	#Cores	#Tasks	\bar{c} (sec)	#Cores	#Tasks	\bar{c} (sec)	#Cores	#Tasks	\bar{c} (sec)	#Cores	#Tasks	\bar{c} (sec)	#Cores	#Tasks	\bar{c} (sec)	
Grid5000 Sites	bordeaux	32	19	189.09	16	10	83.27	20	58	140.63	0	0	0.00	20	114	235.48	62	76	305.95
	lille	16	22	267.36	12	14	586.20	64	76	187.09	16	45	382.61	20	121	282.03	44	105	297.35
	lyon	6	12	17.37	6	8	443.08	24	43	225.83	8	22	671.63	6	62	226.42	6	18	626.19
	nancy	10	31	120.50	0	0	0.00	14	70	125.62	0	0	0.00	10	88	131.01	0	0	0.00
	orsay	10	36	25.82	8	16	337.12	0	0	0.00	4	10	53.91	10	79	289.06	20	83	431.44
	rennes	10	13	38.20	0	0	0.00	14	57	97.41	0	0	0.00	0	0	0.00	0	0	0.00
	sophia	12	24	121.45	40	24	137.55	0	0	0.00	28	58	174.56	20	135	178.10	28	121	467.98
	toulouse	20	27	219.53	12	12	639.25	20	60	249.36	20	29	586.94	20	125	373.87	0	0	0.00
	TOTAL	116	184		94	84		156	364		76	164		106	724		160	403	

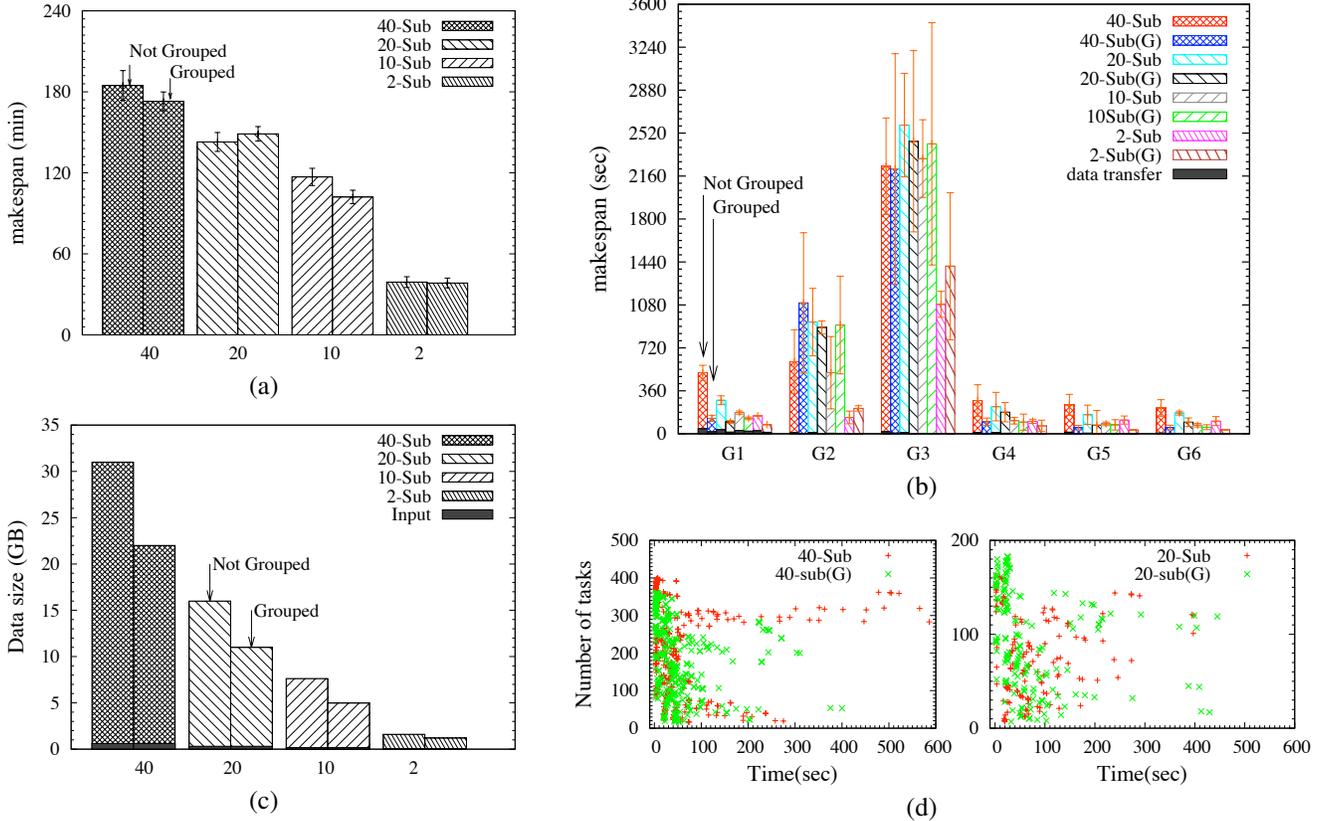


Figure 5: (a) Comparison of makespan of workflow according to the number of subjects used. (b) Comparison of makespan between grouped and ungrouped tasks (see Figure 2 for grouping of tasks). (c) Data size according to the number of subjects used. (d) # of tasks executed vs. Time: Parallelism that was achieved in the system.

able to find the best available resource and then submitted the task to it for execution. Failure of tasks was handled on a per task basis. When tasks failed, they were re-submitted to another resource, which did not have a failure history for those tasks. Although some tasks failed to execute and were rescheduled, their total count was very small.

The workflow was executed multiple times by changing the parameters of the workflow with the help of the Grid Portal. This feature provided flexibility while executing grouped and ungrouped versions of the workflow for each of the 40,20,10 and 2 subjects. Without this feature, orchestrating the whole experiment would have taken a longer amount of time than executing the application on a single machine.

6 Conclusions

In this work, we presented the processing of a compute and data-intensive scientific application in the form of a workflow on the Grid. We implemented the components in the context of executing Image Registration (IR) for fMRI studies. We used the Gridbus Workflow Engine as workflow management system and the Gridbus Broker as the mediator to access the distributed resources. Our experiments demonstrated that the IR procedure can have significantly reduced makespan, greater distribution of storage space and increased flexibility when executed on the Grid. Our analysis and the results of this neuroscience application show that there exists a greater motive and higher potential in strengthening collaboration between eScience communities

and industry.

As part of our continuing efforts, we are enhancing the GWFE to support SLA based workflow scheduling. We are also working on the efficient scheduling of compute and data-intensive scientific workflows on Global Grids.

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APPENDIX

The application script, workflow description in XML, output images and related contents for each subject can be obtained from <http://www.csse.unimelb.edu.au/~spandey/aina2009/index.html> [remember to change to the the "tilde"]