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(54) **METHOD FOR GPU MEMORY MANAGEMENT FOR DEEP NEURAL NETWORK AND COMPUTING DEVICE FOR PERFORMING SAME**

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(57) **ABSTRACT**

Embodiments disclosed herein relate to a method for GPU memory management that observes the deep learning of a deep neural network performed by a GPU and reduces the amount of GPU memory used, thereby overcoming limitations attributable to the memory size of the GPU and allowing the more effective performance of the deep learning, and a computing device for performing the same. According to an embodiment, there is disclosed a method for GPU memory management for a deep neural network, the method being performed by a computing device including a GPU and a CPU, the method including: generating a schedule for GPU memory management based on the processing of a unit operation, included in the deep neural network, by the GPU; and moving data required for deep learning of the deep neural network between GPU memory and CPU memory based on the schedule.

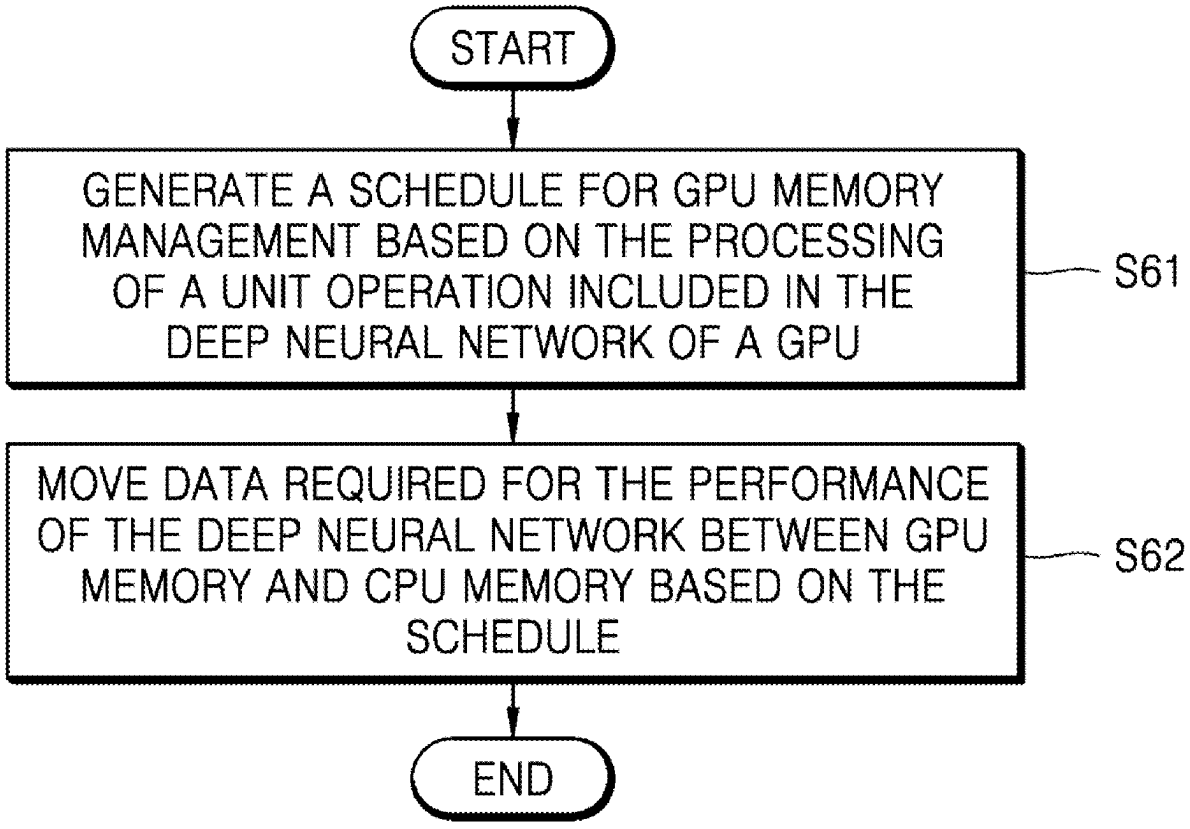


FIG. 1

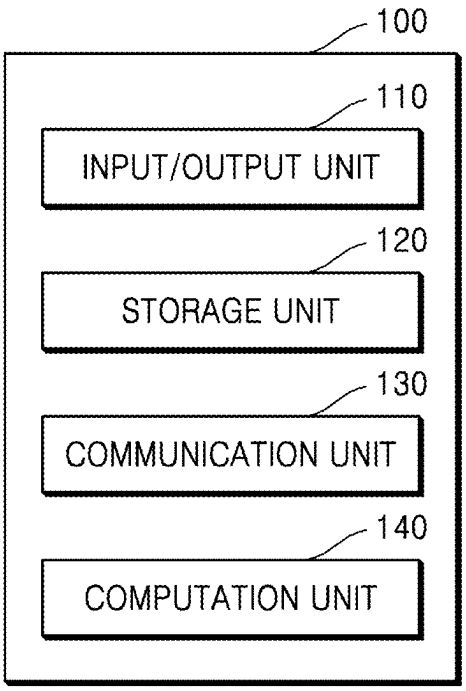

100
110
INPUT/OUTPUT UNIT
120
STORAGE UNIT
130
COMMUNICATION UNIT
140
COMPUTATION UNIT

FIG. 2

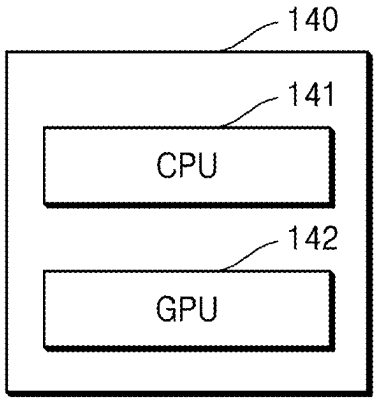


FIG. 3

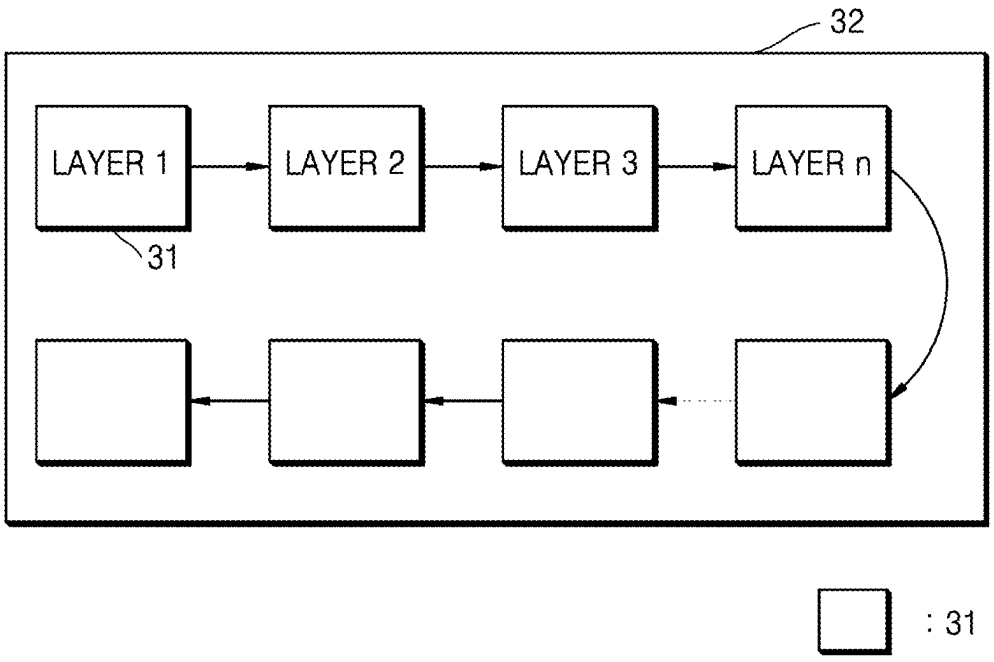


FIG. 4

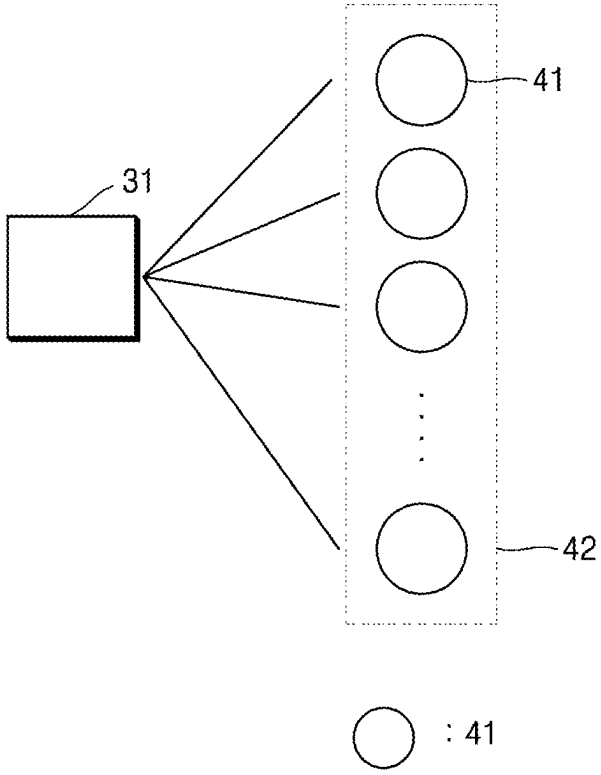


FIG. 5

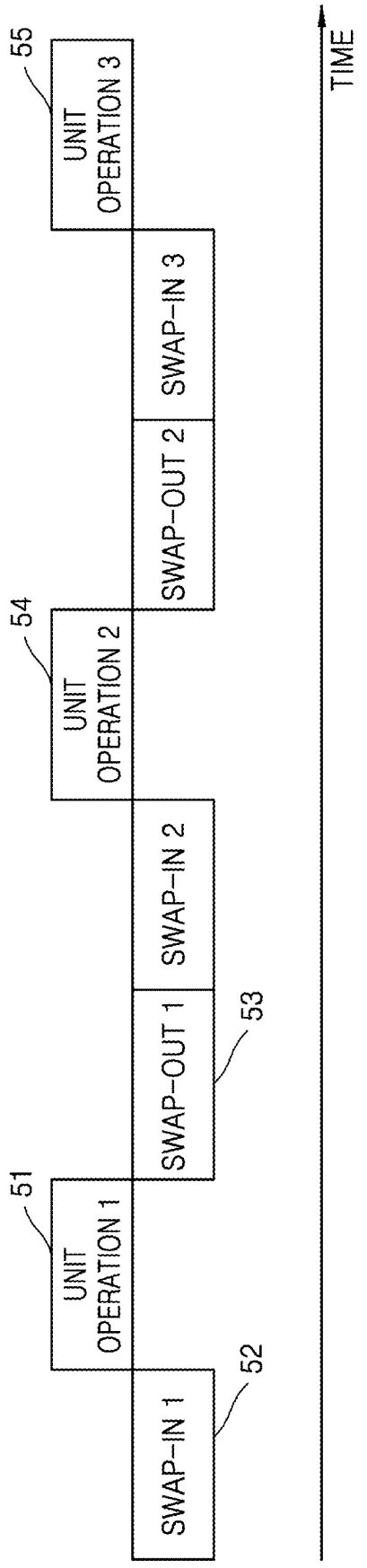

TIME
SWAP-IN 1
52
UNIT OPERATION 1
51
SWAP-OUT 1
53
SWAP-IN 2
UNIT OPERATION 2
54
SWAP-OUT 2
SWAP-IN 3
UNIT OPERATION 3
55

FIG. 6

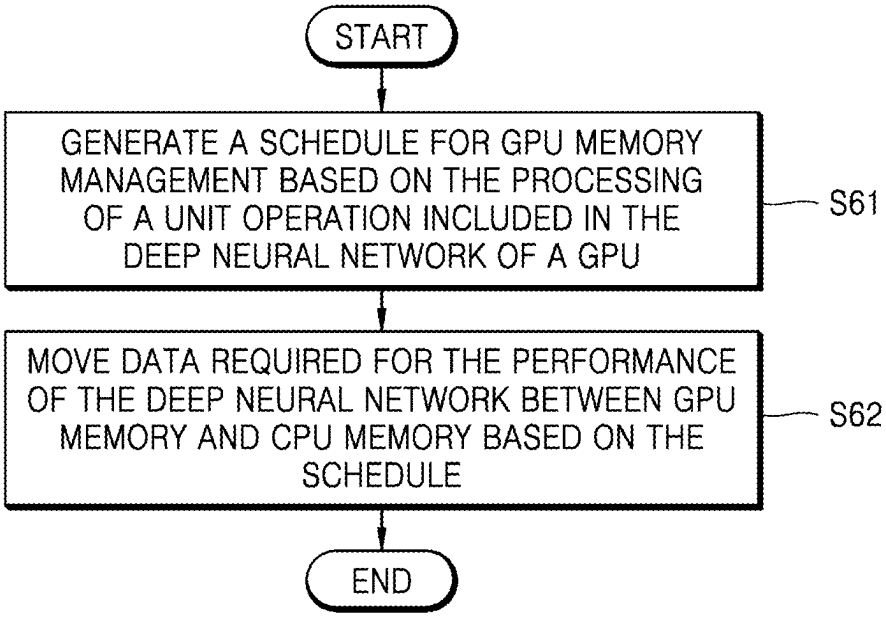

START
GENERATE A SCHEDULE FOR GPU MEMORY MANAGEMENT BASED ON THE PROCESSING OF A UNIT OPERATION INCLUDED IN THE DEEP NEURAL NETWORK OF A GPU
S61
MOVE DATA REQUIRED FOR THE PERFORMANCE OF THE DEEP NEURAL NETWORK BETWEEN GPU MEMORY AND CPU MEMORY BASED ON THE SCHEDULE
S62
END

FIG. 7

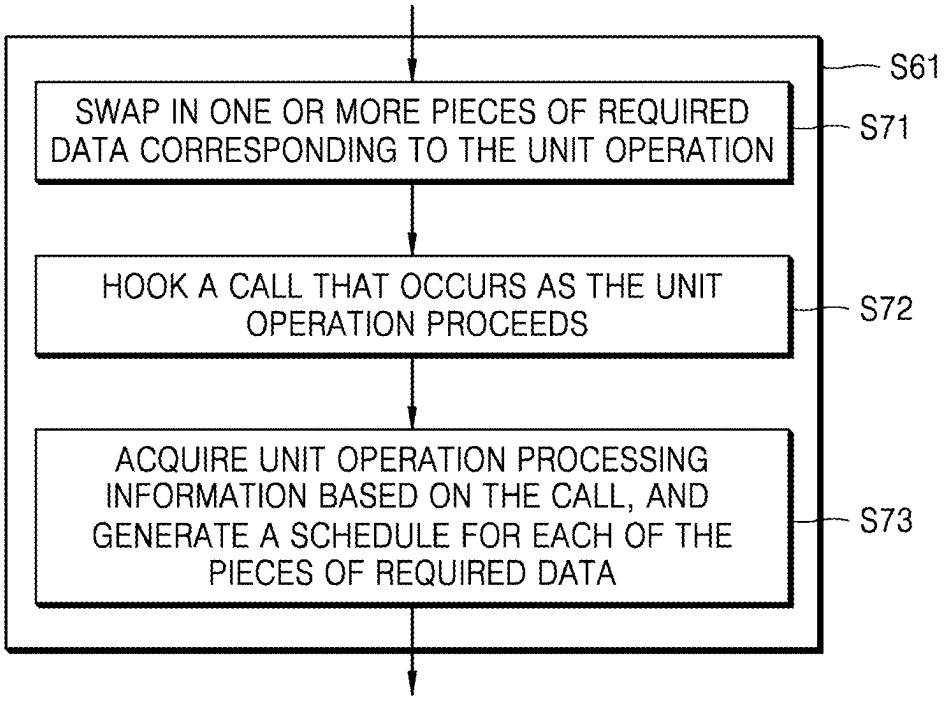

S61
SWAP IN ONE OR MORE PIECES OF REQUIRED DATA CORRESPONDING TO THE UNIT OPERATION
S71
HOOK A CALL THAT OCCURS AS THE UNIT OPERATION PROCEEDS
S72
ACQUIRE UNIT OPERATION PROCESSING INFORMATION BASED ON THE CALL, AND GENERATE A SCHEDULE FOR EACH OF THE PIECES OF REQUIRED DATA
S73

FIG. 8

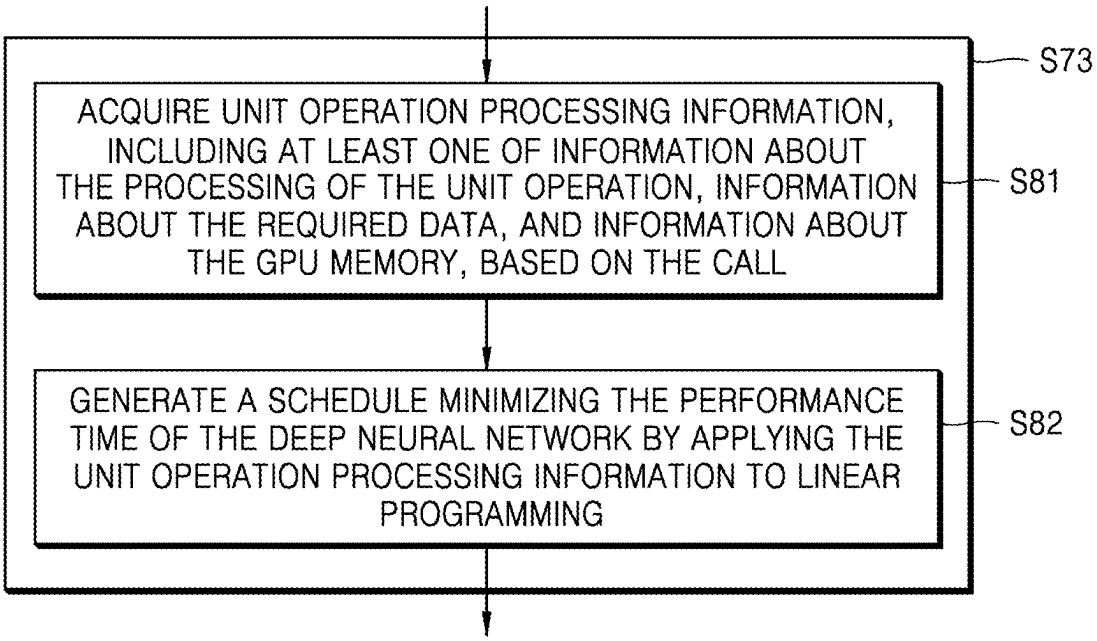
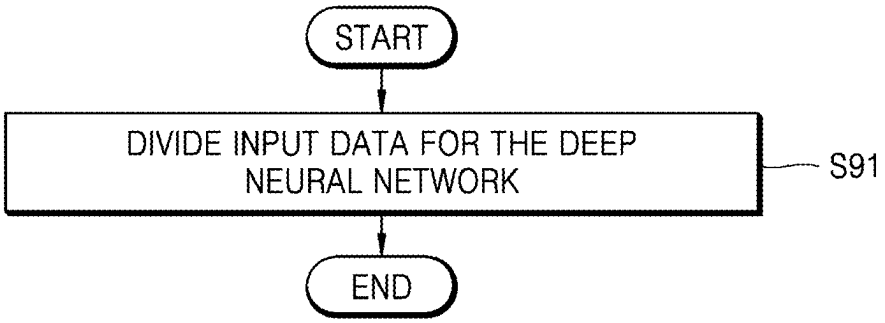

S73
ACQUIRE UNIT OPERATION PROCESSING INFORMATION, INCLUDING AT LEAST ONE OF INFORMATION ABOUT THE PROCESSING OF THE UNIT OPERATION, INFORMATION ABOUT THE REQUIRED DATA, AND INFORMATION ABOUT THE GPU MEMORY, BASED ON THE CALL
S81
GENERATE A SCHEDULE MINIMIZING THE PERFORMANCE TIME OF THE DEEP NEURAL NETWORK BY APPLYING THE UNIT OPERATION PROCESSING INFORMATION TO LINEAR PROGRAMMING
S82

FIG. 9



METHOD FOR GPU MEMORY MANAGEMENT FOR DEEP NEURAL NETWORK AND COMPUTING DEVICE FOR PERFORMING SAME

CROSS REFERENCE TO RELATED APPLICATIONS

[0001] This application is a continuation of U.S. application Ser. No. 16/961,073 filed Jul. 9, 2020, which is a National Stage of International Application No. PCT/KR2018/014894 filed Nov. 29, 2018, claiming priority based on Korean Patent Application No. 10-2018-0003587, filed Jan. 10, 2018.

Technical Field

[0002] Embodiments disclosed herein relate to a method for GPU memory management for a deep neural network and a computing device for performing the same, and particularly to a method for GPU memory management that observes the deep learning of a deep neural network performed by a GPU and reduces the amount of GPU memory used, thereby overcoming a limitation attributable to the memory size of the GPU and allowing deep learning to be more effectively performed, and a computing device for performing the same.

Year 2018 Project Number and Acknowledgements

[0003] 1. Project serial No.: 1711073574

[0004] 2. Korean acknowledgement: "본 연구는 2018년도 정부(과학기술정보통신부)의 재원으로 정보통신기술진흥센터의 지원(No.1711073574, FPGA 클러스터용 CUDA 프로그래밍 환경 기술개발)과 한국연구재단의 지원(2016M3C4A7952587, PF급 이종 초고성능컴퓨터 개발)을 받아 수행된 연구입니다."

[0005] 3. English acknowledgement: "This work was supported by Institute for Information & communications Technology Promotion (IITP) grant funded by the Ministry of Science and ICT (MSIT) (No.1711073574, CUDA Programming Environment for FPGA Clusters), the National Research Foundation of Korea funded by the MSIT (No.2016M3C4A7952587, PF Class Heterogeneous High Performance Computer Development)."

BACKGROUND ART

[0006] Deep learning collectively refers to a number of ways to create and learn a large number of layers in an artificial neural network. Although research into artificial neural networks has been conducted for a long period, they were not put into practical use until the mid-2000s due to their massive computational load. In particular, when deep learning using a deep neural network (DNN) is performed using a GPU, a difficulty arises in that the limitation of the capacity of GPU occurs.

[0007] In connection to this, Korean Patent No. 10-17667875, which is a prior art document, discloses a technology for deep learning based on a GPU, and particularly an 'image correction method using deep learning analysis based on a GPU device.' However, even with the above-described conventional technology, there are still insufficient aspects regarding technology for overcoming the limitation of the capacity of the GPU memory.

[0008] Meanwhile, the above-described background technology corresponds to technical information that has been possessed by the present inventor in order to contrive the present invention or that has been acquired in the process of contriving the present invention, and can not necessarily be regarded as well-known technology that had been known to the public prior to the filing of the present invention.

DISCLOSURE

Technical Problem

[0009] Embodiments disclosed herein are intended to disclose a method for GPU memory management that can overcome the limitation of the capacity of GPU memory, and a computing device for performing the same.

[0010] Furthermore, embodiments are intended to overcome the limitation of GPU memory by utilizing CPU memory when a GPU performs deep learning using a deep neural network.

[0011] Furthermore, embodiments are intended to generate an effective schedule that moves data required for the deep learning of a deep neural network between GPU memory and CPU memory according to the operation processing pattern of a GPU based on the characteristic in which an operation for each layer is repeatedly performed in the deep learning of the deep neural network. In this case, the embodiments are intended to minimize the time by which an operation is delayed due to the movement of data by overlapping the movement of data between the GPU memory and the CPU memory and the operation processing of the GPU.

[0012] Furthermore, embodiments are intended to overcome the limitation of GPU memory by dividing the input data of a deep neural network and reducing a batch size processed by a GPU at one time.

[0013] Moreover, embodiments are intended to secure the transparency of use by performing a method for GPU memory management without the need to modify or recompile the source code of the framework of the conventional deep neural network.

Technical Solution

[0014] As a technical solution for solving the above-described technical problems, according to an embodiment, there is disclosed a method for GPU memory management for a deep neural network, the method being performed by a computing device including a GPU and a CPU, the method including: generating a schedule for GPU memory management based on the processing of a unit operation, included in the deep neural network, by the GPU; and moving data required for deep learning of the deep neural network between GPU memory and CPU memory based on the schedule.

[0015] According to another embodiment, there is disclosed a computer-readable storage medium having stored therein a program that performs a method for GPU memory management. In this case, the method for GPU memory management is performed by a computing device, and may

include: generating a schedule for GPU memory management based on the processing of a unit operation, included in a deep neural network, by a GPU; and moving data required for deep learning of the deep neural network between GPU memory and CPU memory based on the schedule.

[0016] According to still another embodiment, there is disclosed a computer program that is executed by a computing device and stored in a medium to perform a method for GPU memory management. In this case, the method for GPU memory management is performed by a computing device, and may include: generating a schedule for GPU memory management based on the processing of a unit operation, included in a deep neural network, by a GPU; and moving data required for deep learning of the deep neural network between GPU memory and CPU memory based on the schedule.

[0017] According to still another embodiment, there is disclosed a computing device including a computation unit, wherein the computation unit includes a GPU and a CPU, and generates a schedule for GPU memory management based on the processing of a unit operation, included in a deep neural network, by the GPU and moves data required for the deep learning of the deep neural network between GPU memory and CPU memory based on the schedule.

Advantageous Effects

[0018] According to any one of the above-described technical solutions, the embodiments disclosed herein may disclose the method for GPU memory management that can overcome the limitation of the capacity of the GPU memory, and the computing device for performing the same.

[0019] Furthermore, the embodiments may overcome the limitation of the GPU memory by utilizing the CPU memory when the GPU performs deep learning using a deep neural network.

[0020] Furthermore, the embodiments may generate an effective schedule that moves data required for the deep learning of a deep neural network between the GPU memory and the CPU memory according to the operation processing pattern of the GPU based on the characteristic in which an operation for each layer is repeatedly performed in the deep learning of the deep neural network. In this case, the embodiments may minimize the time by which an operation is delayed due to the movement of data by overlapping the movement of data between the GPU memory and the CPU memory and the operation processing of the GPU.

[0021] Furthermore, the embodiments may overcome the limitation of the GPU memory by dividing the input data of a deep neural network and reducing a batch size processed by the GPU at one time.

[0022] Moreover, the embodiments may secure the transparency of use by performing the method for GPU memory management without the need to modify or recompile the source code of the framework of the conventional deep neural network.

[0023] The effects that can be obtained by the embodiments disclosed herein are not limited to the above-described effects, and other effects that have not been described above will be apparently understood by those having ordinary skill in the art, to which the present invention pertains, from the following description.

DESCRIPTION OF DRAWINGS

[0024] FIGS. **1** and **2** are block diagrams showing the configuration of a computing device according to an embodiment;

[0025] FIGS. **3** to **5** are diagrams showing an example of the operation of a computing device according to an embodiment; and

[0026] FIGS. **6** to **9** are flowcharts illustrating methods for GPU memory management according to embodiments.

MODE FOR INVENTION

[0027] Various embodiments will be described in detail below with reference to the accompanying drawings. The following embodiments may be modified to and practiced in various different forms. In order to more clearly illustrate the features of the embodiments, detailed descriptions of items that are well known to those having ordinary skill in the art to the following embodiments pertain will be omitted. In the drawings, portions unrelated to the following description will be omitted. Throughout the specification, like reference symbols will be assigned to like portions.

[0028] Throughout the specification, when one component is described as being "connected" to another component, this includes not only a case where they are 'directly connected' to each other but also a case where they are 'connected to each other with a third component disposed therebetween.' Furthermore, when a component is described as 'including' another component, this does not mean that the former component excludes another component but means that the former component may further include another component, unless explicitly described to the contrary.

[0029] Embodiments will be described in detail below with reference to the accompanying drawings.

[0030] FIG. **1** is a block diagram showing the configuration of a computing device **100** according to an embodiment.

[0031] According to the embodiment of the present specification, the computing device **100** includes a graphics processing unit (GPU) for performing deep learning using a deep neural network (DNN), and performs a method for GPU memory management in order to overcome the limitation of GPU memory when the GPU performs deep learning using a deep neural network.

[0032] Referring to FIG. **1**, the computing device **100** according to the embodiment may include an input/output unit **110**, a storage unit **120**, a communication unit **130**, and a computation unit **140**.

[0033] The input/output unit **110** according to an embodiment may include an input unit for receiving input from a user, and an output unit for displaying information about the result of the performance of computation, e.g., the result of the performance of deep learning by a deep neural network. For example, the input/output unit **110** may include an operation panel configured to receive input from a user, and a display panel configured to output images.

[0034] More specifically, the input unit may include various types of input reception devices such as a keyboard, physical buttons, a touch screen, or a camera. Furthermore, the output unit may include a display panel, a speaker, or a headset. However, the input/output unit **110** is not limited to the above-described examples, but may include configurations configured to support various types of input and output.

[0035] Meanwhile, various types of data for the deep learning of a deep neural network may be installed and stored in the storage unit **120**. According to an embodiment, the storage unit **120** may store input data, i.e., a target of a deep neural network, intermediate data, and the result data of deep learning, and may store and run software such as an application and/or a device driver for the deep learning of a deep neural network. According to an embodiment, the storage unit **120** may be embedded in at least one of a GPU and a CPU included in the computation unit **140** to be described later.

[0036] Meanwhile, the communication unit **130** may perform wired/wireless communication with another device or network. For this purpose, the communication unit **130** may include a communication module configured to support at least one of various wired/wireless communication methods. For example, the communication module may be implemented in the form of a chipset.

[0037] The wireless communication supported by the communication unit **130** may be, e.g., wireless fidelity (Wi-Fi), Wi-Fi Direct, Bluetooth, ultra-wide band (UWB), or near field communication (NFC). Furthermore, the wired communication supported by the communication unit **130** may be, e.g., USB or high definition multimedia interface (HDMI).

[0038] According to an embodiment, the communication unit **130** may receive input data, which is a target of a deep neural network, from a third server.

[0039] Meanwhile, the computation unit **140** may control the overall operation of the computing device **100**. According to an embodiment, the computing unit **140** may control other components included in the computing device **100** to perform deep learning using a deep neural network, and may process various types of data to perform deep learning using a deep neural network. In this case, the deep learning may include the learning and inference of a deep neural network.

[0040] In this case, FIG. **2** is a block diagram illustrating an embodiment of the computation unit **140**. Referring to FIG. **2**, the computation unit **140** may include processors such as a CPU **141** and a GPU **142**. According to an embodiment, each of the CPU **141** and the GPU **142** may include embedded memory. In other words, the CPU **141** may include CPU memory, and the GPU **142** may include GPU memory.

[0041] In this case, referring to FIG. **3**, FIG. **3** is a view schematically showing an example of the configuration of a deep neural network. Referring to FIG. **3**, the deep neural network includes a plurality of layers **31**. The deep neural network (DNN) includes all neural networks each having three or more layers, including not only a neural network including fully connected layers (FC layers) but also a convolution neural network (CNN) and a recurrent neural network (RNN). A computation process processed in each layer included in the deep neural network is referred to as a 'unit operation.' According to an embodiment, a unit operation may be implemented as a predetermined function, in which case the predetermined function may be implemented as a CUDA kernel or an OpenCL kernel and may be provided in a library form such as cuDNN or cuBlas.

[0042] Furthermore, the deep learning of the deep neural network may repeat the process of sequentially performing unit operations corresponding to the plurality of respective layers **31**. In this case, a process including the plurality of repeated layers is referred to as an 'iteration **32**.' In other words, the deep learning of the deep neural network may include the process of repeating a unit operation corresponding to each of the plurality of layers **31** by repeating the iteration **32** including the plurality of layers **31** a plurality of times.

[0043] In this case, according to an embodiment, the above-described deep learning using a deep neural network may be performed by the GPU **142**. In other words, the GPU **142** may perform the deep learning using a deep neural network by repeating an iteration adapted to sequentially perform a plurality of unit operations.

[0044] In this case, referring to FIG. **4**, FIG. **4** is a diagram schematically illustrating an example of the relationship between a unit operation and 'required data **41**,' i.e., information required for the performance of the unit operation. Referring to FIG. **4**, each unit operation may match one or more pieces of required data **41**. Furthermore, a data unit including one or more pieces of required data **41** corresponding to one unit operation is referred to as a 'required data bundle **42**.' According to an embodiment, the required data **41** may include input data, a weight value used in each layer, and an intermediate result (a feature map) output in each layer.

[0045] Meanwhile, the GPU **142** may receive the required data **41** or required data bundle **42** before or during each unit operation via the GPU memory when performing the unit operation. Furthermore, the GPU **142** may perform deep learning using a deep neural network by performing the unit operation based on the required data **41** received by the GPU memory. In this case, the performance of the GPU **142** achieved when the GPU **142** performs deep learning using a deep neural network may be dependent upon the management of the GPU memory.

[0046] In the conventional deep learning using a deep neural network, the deep learning is performed to process required data with all required data corresponding to all unit operations input to GPU memory. In this case, when the size of the GPU memory is smaller than the overall size of all the required data, deep learning cannot be performed.

[0047] Accordingly, according to an embodiment, the computation unit **140** attempts to perform deep learning using a deep neural network requiring a large amount of memory with minimal performance degradation by performing a method for GPU memory management. In connection with this, the method for GPU memory management performed by the computation unit **140** will be described in detail below. The method for GPU memory management described below may be controlled by the CPU **141** included in the computation unit **140** or by the GPU **142** according to an embodiment.

[0048] According to an embodiment, the computation unit **140** may move data required for the deep learning of a deep neural network between the GPU memory and the CPU memory in order to effectively utilize the GPU memory. For example, the computation unit **140** may move required data from the CPU memory to the GPU memory or from the GPU memory to the CPU memory. In this case, the term 'swap in' means to move the required data to be processed from the CPU memory to the GPU memory, and the term 'swap in' means to move the required data to be processed from the GPU memory to the CPU memory.

[0049] Meanwhile, the computation unit **140** may generate a GPU memory management schedule for the purpose of managing the GPU memory. According to an embodiment,

the computation unit **140** may generate a schedule for GPU memory management, and, more specifically, may generate a schedule based on the processing of unit operations included in the deep neural network of the GPU **142**.

[0050] As described above, the GPU **142** may sequentially perform one or more unit operations by repeating an iteration including the one or more unit operations, and may also repeatedly perform the unit operations.

[0051] In this case, the computation unit **140** may generate a schedule based on the repeated processing of unit operations corresponding to the set number of times, and may apply the generated schedule to the repeated processing of the unit operations after the set number of times. In other words, the computation unit **140** may generate a schedule based on information about the processing of unit operations acquired based on the processing of the unit operations in the initial stage of an iteration when the unit operations are repeated a plurality of times. Furthermore, the computation unit **140** may apply the generated schedule to the unit operations to be repeated after the schedule has been generated.

[0052] In this case, referring to FIG. **5**, FIG. **5** is a diagram schematically illustrating an example of a process of the initial iteration of unit operations for the generation of a schedule. According to FIG. **5**, the computation unit **140** may swap in (see **52**) one or more pieces of required data corresponding to a unit operation before performing a unit operation **51**. For example, the computation unit **140** may collectively swap in (see **52**) one or more pieces of required data corresponding to the unit operation **51**.

[0053] Furthermore, the computation unit **140** may hook a call occurring as the unit operation **51** proceeds based on the swapped-in (see **52**) required data. In this case, the computation unit **140** may acquire unit operation processing information based on the call, and may generate a schedule for each piece of required data based on the acquired unit operation processing information.

[0054] Furthermore, when the unit operation **51** is completed, the computation unit **140** may swap out (see **53**) the processed required data. For example, the computation unit **140** may perform the unit operation **51** based on the swapped-in (see **51**) required data, and, then, may collectively swap out (see **53**) the processed one or more pieces of required data.

[0055] Furthermore, the computation unit **140** may sequentially perform subsequent operations **54** and **55** after the unit operation according to the performance of the deep learning of a deep neural network. In this case, the computation unit **140** may perform the above-described swap-in and swap-out processes for each of the subsequent operations **54** and **55**, and may acquire unit operation processing information corresponding to each of the unit operations.

[0056] According to an embodiment, the unit operation processing information may include at least one of information about the performance of a unit operation, information about required data, and information about GPU memory. In this case, the information about the performance of a unit operation unit may include the performance time of the unit operation, the sequential position of the performance of the unit operation, a function corresponding to the unit operation, and information about required data matching the unit operation, e.g., information adapted to specify required data matching the unit operation. Furthermore, the information about required data may include the size of the required data, and the movement time of the required data between the GPU memory and the CPU memory. Furthermore, the information about GPU memory may include the size of the GPU memory.

[0057] According to an embodiment, the computation unit **140** may reduce the processing time of the unit operation by performing the swap-in and swap-out of the required data together with the unit operation in an overlapping manner based on the acquired unit operation processing information.

[0058] For this purpose, the computation unit **140** may apply the acquired unit operation processing information to linear programming (LP). In this case, the linear programming may include integer linear programming (ILP).

[0059] LP is a technique that is used to maximize or minimize a linear objective function while satisfying linear conditions given as a type of optimization problems. For example, when a linear equation is established between variable elements (when variable elements have linear relationships), an inequality may be established using the limit of change, and the value of a variable that minimizes or maximizes a predetermined objective function may be acquired. According to an embodiment, LP may solve problems using a commercial solver.

[0060] According to an embodiment, the computation unit **140** may generate an inequality based on ILP to which the acquired unit work processing information is applied, and may derive a schedule minimizing the performance time of the deep learning of a deep neural network by allowing the movement of required data and the operation of deep learning to overlap each other as much as possible.

[0061] Meanwhile, according to an embodiment, the computation unit **140** may generate a schedule based on a heuristic technique. In this case, if the time required for a swap-in and a swap-out exceeds the processing time of a unit operation when swapping in one or more pieces of required data corresponding to a unit operation and swapping out required data processed according to a unit operation, the computation unit **140** may search for a swap-in command that can be processed in an operation preceding the unit operation and generate a schedule so that the swap-in command will be processed during the performance of the preceding operation.

[0062] According to a more specific embodiment, the computation unit **140** may sequentially perform a plurality of unit operations, may swap in necessary required data during each unit operation, and may swap out processed required data during each unit operation.

[0063] In this case, the computation unit **140** may detect an 'excess unit operation' in which the time required for a swap-in and a swap-out exceeds the processing time of a unit operation among unit operations, may search for a swap-in command corresponding to the excess unit operation, and may search for an operation that precedes the excess unit operation and can be processed along with the found swap-in command in an overlapping manner. In this case, the operation that precedes the excess unit operation and can be processed along with the found swap-in command corresponding to the excess unit operation in an overlapping manner is referred to as an 'excess preceding operation.'

[0064] According to an embodiment, the computation unit **140** may generate a schedule so that a swap-in command corresponding to an excess unit operation overlaps an excess preceding operation. In this case, the computation unit **140** may search for an excess preceding operation, more par-

ticularly an excess preceding operation to be overlapped by the processing time of a swap-in command corresponding to an excess unit operation as much as possible, and may generate a schedule based on the excess preceding operation.

[0065] Furthermore, according to an embodiment, when a swap-out command for the same required data is found while searching for an excess preceding operation, the computation unit **140** may prevent unnecessary communication by eliminating a swap-in command and the swap-out command.

[0066] According to an embodiment, the computation unit **140** may repeat a unit operation and update a schedule when searching for an excess preceding operation and generating the schedule so that the processing time of a swap-in command is overlapped. In this case, the computation unit **140** may repeat an iteration until there is no change in a schedule any longer, may search for an excess preceding operation, and may apply a generated schedule to subsequent unit operations and repeating an iteration after the generation of the schedule, thereby performing deep learning using a deep neural network.

[0067] When the method for GPU memory management based on the heuristic technique and the method for GPU memory management based on LP according to embodiments are compared with each other, LP can derive an optimum value, but requires a longer time to derive an optimum value than the heuristic technique. In contrast, the heuristic technique can derive a value close to an optimum value, not the optimum value, but has an advantage in that it requires a shorter time to derive a result value than LP.

[0068] Meanwhile, the computation unit **140** may reduce a batch size to be processed in the GPU **142** at one time by dividing input data for the performance of deep learning using a deep neural network. For example, the computation unit **140** may divide input data including 256 batches into 4 pieces of input data each including 64 batches. In this case, the computation unit **140** may derive result data (an output feature map) by performing deep learning using a deep neural network including unit operations based on each of the divided four pieces of input data.

[0069] According to an embodiment, the computation unit **140** may perform a unit operation, and may swap in required data corresponding to the corresponding unit operation or an operation subsequent to the corresponding unit operation or swap out required data processed in the GPU **142**, based on the generated schedule.

[0070] According to an embodiment, the above-described method for GPU memory management does not need to modify or recompile the source code of the framework of the conventional deep neural network. For this purpose, the computation unit **140** may perform the above-described method for GPU memory management based on a shared library form. For example, the computation unit may allocate and release the memory of the framework of the deep neural network by performing a swap-in and a swap-out via a shared library, and may hook calls to unit operations in the middle, thereby performing memory management. In addition, calls to commercial libraries, such as cuDNN and cuBlas, the source code of which has not been disclosed may be intercepted to manage memory.

[0071] Meanwhile, FIGS. **6** to **9** are flowcharts illustrating a method for GPU memory management that is performed by the computing device **100**. The methods for GPU memory management according to the embodiments shown in FIGS. **6** to **9** include the steps that are performed in a time-series manner by the computing device **100** according to the embodiments of FIGS. **1** to **5**. Accordingly, the descriptions that will be omitted below but have been given above in conjunction with the computing device **100** according to the embodiments of FIGS. **1** to **5** may be also applied to the methods for GPU memory management according to the embodiments shown in FIGS. **6** to **9**.

[0072] Referring to FIG. **6**, the computing device **100** may generate a schedule for GPU memory management based on the processing of a unit operation included in the deep neural network of the GPU **142** at step S**61**.

[0073] Furthermore, the computing device **100** may move required data necessary for the performance of the deep learning of a deep neural network between the GPU memory and the CPU memory based on the schedule at step S**62**. In this case, at step S**62**, the computing device **100** may perform a unit operation, and may swap in required data corresponding to the unit operation or an operation subsequent to the unit operation from the CPU memory to the GPU memory or swap out required data processed in the GPU **142** from the GPU memory to the CPU memory, based on the generated schedule.

[0074] According to an embodiment, the deep learning of a deep neural network is performed by repeating an iteration including one or more unit operations a plurality of times. According to this feature, the computing device **100** may generate a schedule based on the repeated processing of unit operations corresponding to the number of times set at step S**61**, and may apply the schedule to the repeated processing of unit operations after the number of times set at step S**62**.

[0075] Meanwhile, referring to FIG. **7**, the computing device **100** may swap in one or more pieces of required data corresponding to the unit operation at step S**71** when generating the schedule at step S**61**. In this case, the computing device **100** may hook a call occurring as the unit operation proceeds at step S**72**, and may acquire unit operation processing information based on the call and generate a schedule for each piece of required data at step S**73**.

[0076] In connection with this, referring to FIG. **8**, the computing device **100** may acquire unit operation processing information including at least one of information about the performance of the unit operation, information about the required data, and information about the GPU memory at step S**81**, and may generate a schedule minimizing the performance time of the deep learning by a deep neural network by applying the acquired unit operation processing information to LP at step S**82**.

[0077] Furthermore, according to an embodiment, if the time required for a swap-in and a swap-out exceeds the processing time of the unit operation when swapping in one or more pieces of required data corresponding to the unit operation and swapping out required data processed according to the unit operation in order to generate the schedule at step S**61**, the computing device **100** may search for a swap-in command that can be processed in an operation preceding the unit operation and generate a schedule so that the swap-in command can be processed during the performance of the preceding operation.

[0078] Meanwhile, referring to FIG. **9**, the computing device **100** may divide input data for the deep learning of a deep neural network at step S**91**. According to an embodi-

ment, the computing device **100** may perform a method for GPU memory management after step S**61** based on the divided input data.

[0079] The term 'unit' used in the above-described embodiments means software or a hardware component such as a field-programmable gate array (FPGA) or application-specific integrated circuit (ASIC), and a 'unit' performs a specific role. However, a 'unit' is not limited to software or hardware. A 'unit' may be configured to be present in an addressable storage medium, and also may be configured to run one or more processors. Accordingly, as an example, a 'unit' includes components, such as software components, object-oriented software components, class components and task components, processes, functions, attributes, procedures, subroutines, segments in program code, drivers, firmware, microcode, circuits, data, a database, data structures, tables, arrays, and variables.

[0080] Each of the functions provided in components and 'unit(s)' may be coupled to a smaller number of components and 'unit(s)' or divided into a larger number of components and 'unit(s).'

[0081] In addition, components and 'unit(s)' may be implemented to run one or more CPUs in a device or secure multimedia card.

[0082] Each of the methods for GPU memory management according to the embodiments described with reference to FIGS. **6** to **9** may be implemented in the form of a computer-readable medium that stores instructions and data that can be executed by a computer. In this case, the instructions and the data may be stored in the form of program code, and may generate a predetermined program module and perform a predetermined operation when executed by a processor. Furthermore, the computer-readable medium may be any type of available medium that can be accessed by a computer, and may include volatile, non-volatile, separable and non-separable media. Furthermore, the computer-readable medium may be a computer storage medium. The computer storage medium may include all volatile, non-volatile, separable and non-separable media that store information, such as computer-readable instructions, a data structure, a program module, or other data, and that are implemented using any method or technology. For example, the computer storage medium may be a magnetic storage medium such as an HDD, an SSD, or the like, an optical storage medium such as a CD, a DVD, a Blu-ray disk or the like, or memory included in a server that can be accessed over a network.

[0083] Furthermore, each of the methods for GPU memory management according to the embodiments described with reference to FIGS. **6** to **9** may be implemented as a computer program (or a computer program product) including computer-executable instructions. The computer program includes programmable machine instructions that are processed by a processor, and may be implemented as a high-level programming language, an object-oriented programming language, an assembly language, a machine language, or the like. Furthermore, the computer program may be stored in a tangible computer-readable storage medium (for example, memory, a hard disk, a magnetic/optical medium, a solid-state drive (SSD), or the like).

[0084] Accordingly, each of the methods for GPU memory management according to the embodiments described with reference to FIGS. **6** to **9** may be implemented in such a manner that the above-described computer program is executed by a computing apparatus. The computing apparatus may include at least some of a processor, memory, a storage device, a high-speed interface connected to memory and a high-speed expansion port, and a low-speed interface connected to a low-speed bus and a storage device. These individual components are connected using various buses, and may be mounted on a common motherboard or using another appropriate method.

[0085] In this case, the processor may process instructions within a computing apparatus. An example of the instructions is instructions which are stored in memory or a storage device in order to display graphic information for providing a Graphic User Interface (GUI) onto an external input/output device, such as a display connected to a high-speed interface. As another embodiment, a plurality of processors and/or a plurality of buses may be appropriately used along with a plurality of pieces of memory. Furthermore, the processor may be implemented as a chipset composed of chips including a plurality of independent analog and/or digital processors.

[0086] Furthermore, the memory stores information within the computing device. As an example, the memory may include a volatile memory unit or a set of the volatile memory units. As another example, the memory may include a non-volatile memory unit or a set of the non-volatile memory units. Furthermore, the memory may be another type of computer-readable medium, such as a magnetic or optical disk.

[0087] In addition, the storage device may provide a large storage space to the computing device. The storage device may be a computer-readable medium, or may be a configuration including such a computer-readable medium. For example, the storage device may also include devices within a storage area network (SAN) or other elements, and may be a floppy disk device, a hard disk device, an optical disk device, a tape device, flash memory, or a similar semiconductor memory device or array.

[0088] The above-described embodiments are intended for illustrative purposes. It will be understood that those having ordinary knowledge in the art to which the present invention pertains can easily make modifications and variations without changing the technical spirit and essential features of the present invention. Therefore, the above-described embodiments are illustrative and are not limitative in all aspects. For example, each component described as being in a single form may be practiced in a distributed form. In the same manner, components described as being in a distributed form may be practiced in an integrated form.

[0089] The scope of protection pursued via the present specification should be defined by the attached claims, rather than the detailed description. All modifications and variations which can be derived from the meanings, scopes and equivalents of the claims should be construed as falling within the scope of the present invention.

1. A computer-implemented method for graphics processing unit (GPU) memory management for a deep neural network, the method being performed by a computing device including a GPU and a central processing unit (CPU), the method comprising:

generating a schedule for GPU memory management based on processing of a unit operation, wherein the

unit operation is a computation process processed by the GPU in each layer included in the deep neural network;

performing the unit operation repeatedly by the GPU and moving a data required for deep learning of the deep neural network by swapping in the data from CPU memory to GPU memory, or swapping out the data, which is processed on the GPU, to the CPU memory, based on the schedule; and

utilizing the CPU memory when the GPU performs the deep learning of the deep neural network, so as to overcome a limitation of the GPU memory,

wherein the generating the schedule comprises:

determining the unit operation as an excess unit operation if a time required for swapping in one or more pieces of required data corresponding to the unit operation and swapping out one or more pieces of required data processed according to the unit operation exceeds a processing time of the unit operation,

searching for a swap-in command corresponding to the excess unit operation and searching for an excess preceding operation that precedes the excess unit operation to be processed along with the swap-in command corresponding to the excess unit operation in an overlapping manner, and

generating the schedule so that the swap-in command corresponding to the excess unit operation is processed during performance of the excess preceding operation.

2. The computer-implemented method of claim **1**, wherein the moving the data comprises:

swapping in the data required for deep learning of the deep neural network from the CPU memory to the GPU memory, the swapping in the data corresponding to at least one of the unit operation and an operation subsequent to the unit operation from the CPU memory to the GPU memory based on the schedule.

3. The computer-implemented method of claim **1**, wherein:

generating the schedule comprises generating the schedule based on repeated processing of the unit operation corresponding to a set number of times; and

moving the data comprises applying the schedule to repeated processing of the unit operation after the set number of times.

4. The computer-implemented method of claim **1**, further comprising, before generating the schedule, dividing input data for the deep neural network;

wherein generating the schedule is performed on each of pieces of the divided input data.

5. A non-transitory computer-readable storage medium having stored thereon a program that performs the method set forth in claim **1**.

6. A computer program that is executed by the computing device and stored in a non-transitory computer-readable storage medium to perform the method set forth in claim **1**.

7. A computing device comprising:

a central processing unit (CPU);

a CPU memory operatively connected to the CPU;

a graphics processing unit (GPU); and

a GPU memory operatively connected to the GPU,

wherein the GPU is configured to:

generate a schedule for GPU memory management based on processing of a unit operation, wherein the unit operation is a computation process processed by the GPU in each layer included in a deep neural network,

perform the unit operation repeatedly on the GPU and move a data required for deep learning of the deep neural network by swapping in the data from the CPU memory to the GPU memory, or swapping out the data, which is processed on the GPU, to the CPU memory, based on the schedule, and

utilize the CPU memory when the GPU performs the deep learning of the deep neural network, so as to overcome a limitation of the GPU memory,

wherein the GPU is further configured to:

determine the unit operation as an excess unit operation if a time required for swapping in one or more pieces of required data corresponding to the unit operation and swapping out one or more pieces of required data processed according to the unit operation exceeds a processing time of the unit operation,

search for a swap-in command corresponding to the excess unit operation and search for an excess preceding operation that precedes the excess unit operation to be processed along with the swap-in command corresponding to the excess unit operation in an overlapping manner, and

generate the schedule so that the swap-in command corresponding to the excess unit operation is processed during performance of the excess preceding operation.

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