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Shen et al.

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(54) DEPTH-BASED SEE-THROUGH PREVENTION IN IMAGE FUSION

(71) Applicant: **INNOPEAK TECHNOLOGY, INC.**, Palo Alto, CA (US)

(72) Inventors: **Jinglin Shen**, Palo Alto, CA (US); **Kim C. Ng**, Palo Alto, CA (US); **Jinsong Liao**, Palo Alto, CA (US); **Chiuman Ho**, Palo Alto, CA (US)

(73) Assignee: **INNOPEAK TECHNOLOGY, INC.**, Palo Alto, CA (US)

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G06T 3/40	(2006.01)

(52) **U.S. Cl.**

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(58) **Field of Classification Search**

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(Continued)

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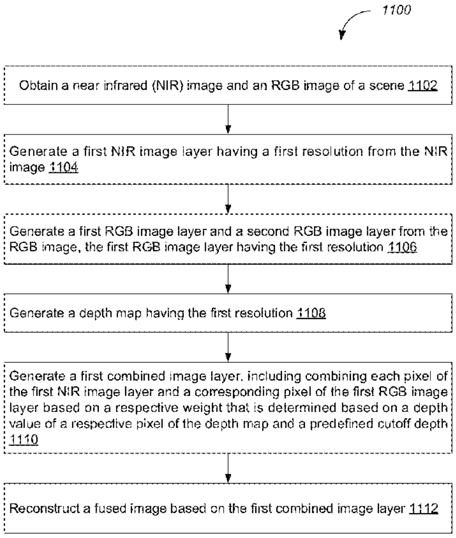
Primary Examiner — Phuoc Tran
(74) *Attorney, Agent, or Firm* — Hodgson Russ LLP

(57) ABSTRACT

This disclosure is directed to image fusion. A computer system obtains a near infrared (NIR) image and an RGB image of a scene. A first NIR image layer is generated from the NIR image. A first RGB image layer and a second RGB image layer are generated from the RGB image. The first NIR image layer and first RGB image layer have a first resolution. A depth map is also generated and has the first resolution. Each pixel of the first NIR image layer and a corresponding pixel of the first RGB image layer are combined based on a respective weight to generate a first combined image layer used to reconstruct a fused image. For each pair of pixels of the first NIR and RGB layers, the respective weight is determined based on a depth value of a respective pixel of the depth map and a predefined cutoff depth.

20 Claims, 11 Drawing Sheets


1100
Obtain a near infrared (NIR) image and an RGB image of a scene 1102
Generate a first NIR image layer having a first resolution from the NIR image 1104
Generate a first RGB image layer and a second RGB image layer from the RGB image, the first RGB image layer having the first resolution 1106
Generate a depth map having the first resolution 1108
Generate a first combined image layer, including combining each pixel of the first NIR image layer and a corresponding pixel of the first RGB image layer based on a respective weight that is determined based on a depth value of a respective pixel of the depth map and a predefined cutoff depth 1110
Reconstruct a fused image based on the first combined image layer 1112

Related U.S. Application Data

(60) Provisional application No. 63/113,624, filed on Nov. 13, 2020, provisional application No. 63/113,168, filed on Nov. 12, 2020.

(52) **U.S. Cl.**
CPC *G06T 2207/10048* (2013.01); *G06T 2207/20016* (2013.01); *G06T 2207/20221* (2013.01)

(58) **Field of Classification Search**
CPC . G06T 2207/20221; G06T 2207/20081; G06T 2207/20084; G06T 7/55
See application file for complete search history.

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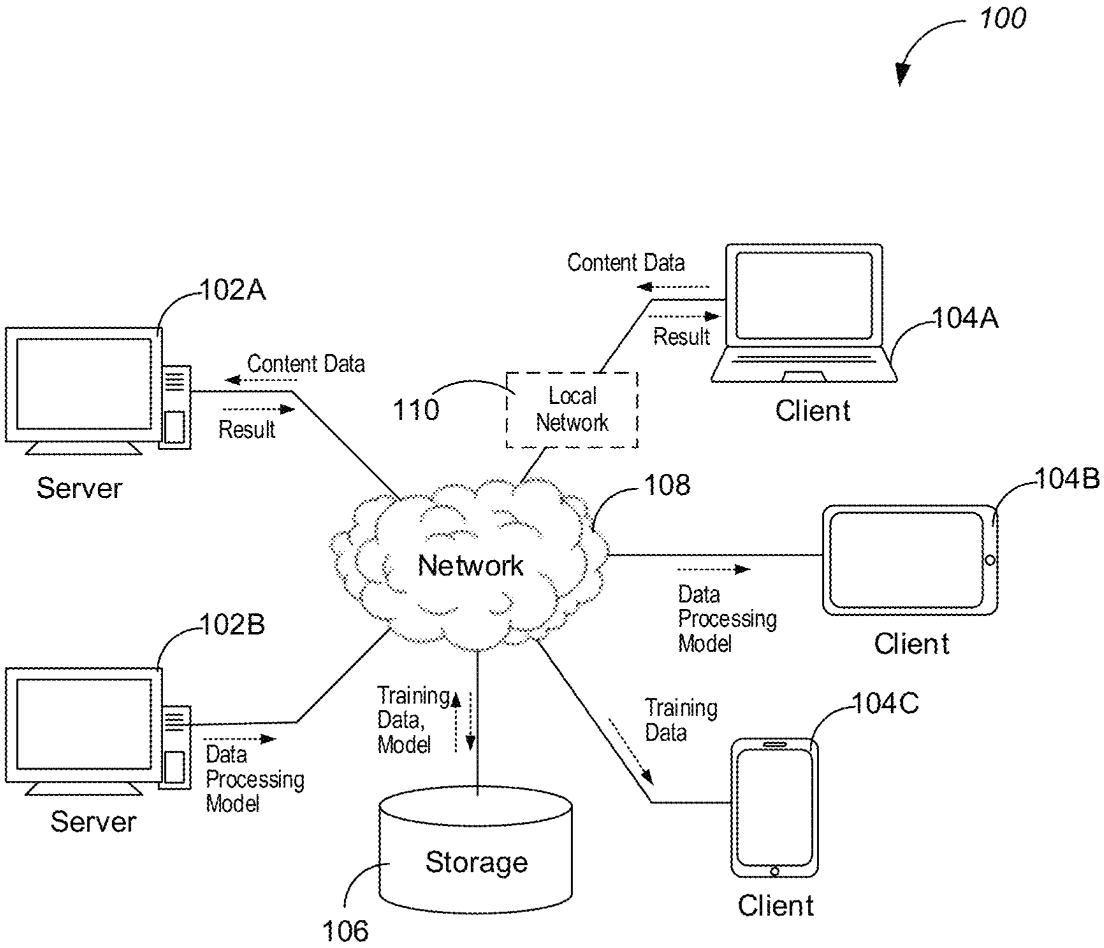

100
102A
Server
Content Data
Result
110
Local Network
Content Data
Result
104A
Client
108
Network
104B
Data Processing Model
Client
102B
Server
Data Processing Model
Training Data, Model
Training Data
104C
Storage
106
Client

FIG 1

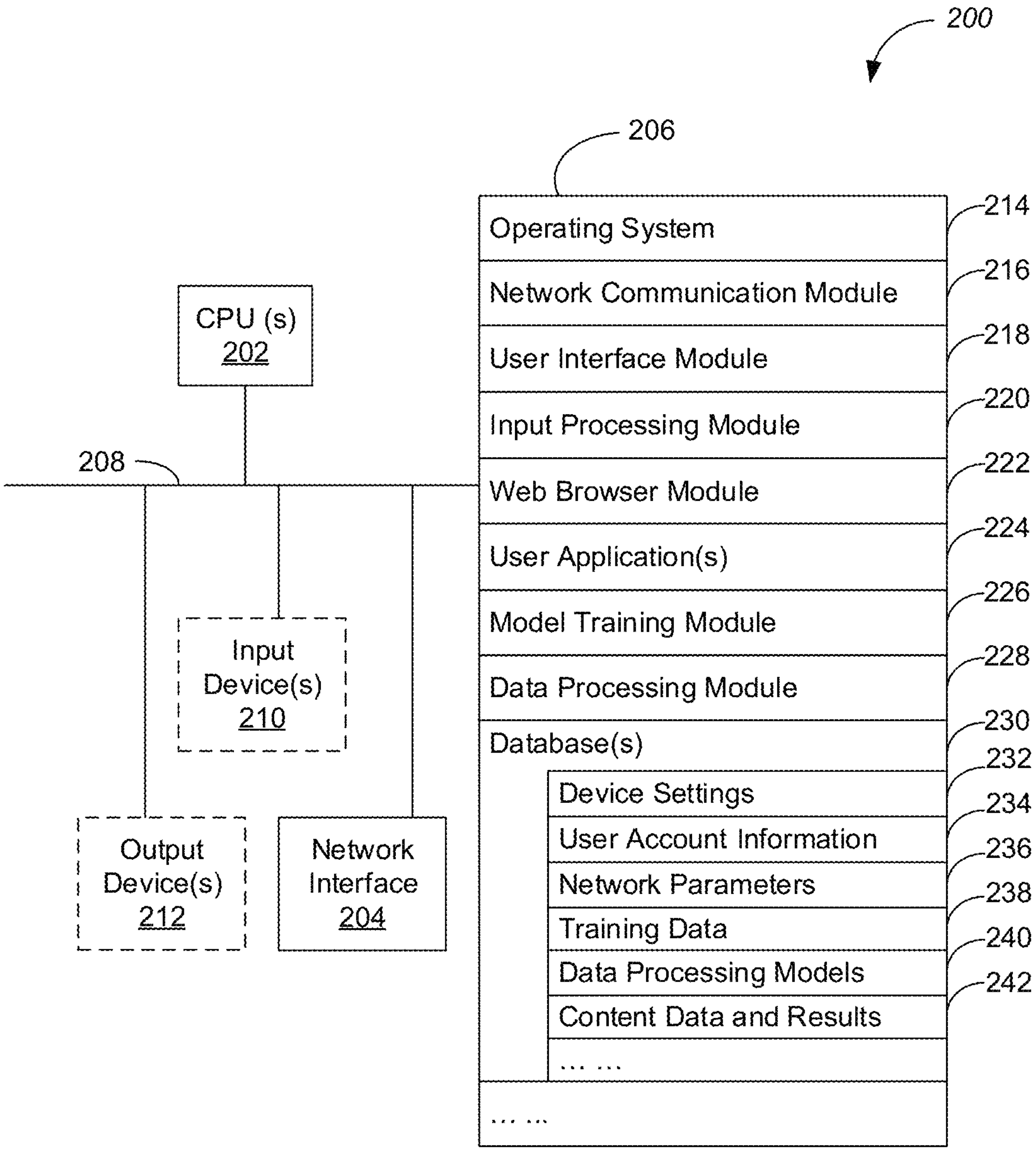

200
206
Operating System
214
Network Communication Module
216
User Interface Module
218
Input Processing Module
220
Web Browser Module
222
User Application(s)
224
Model Training Module
226
Data Processing Module
228
Database(s)
230
Device Settings
232
User Account Information
234
Network Parameters
236
Training Data
238
Data Processing Models
240
Content Data and Results
242
… …
… …
CPU (s)
202
208
Input
Device(s)
210
Output
Device(s)
212
Network
Interface
204

FIG 2

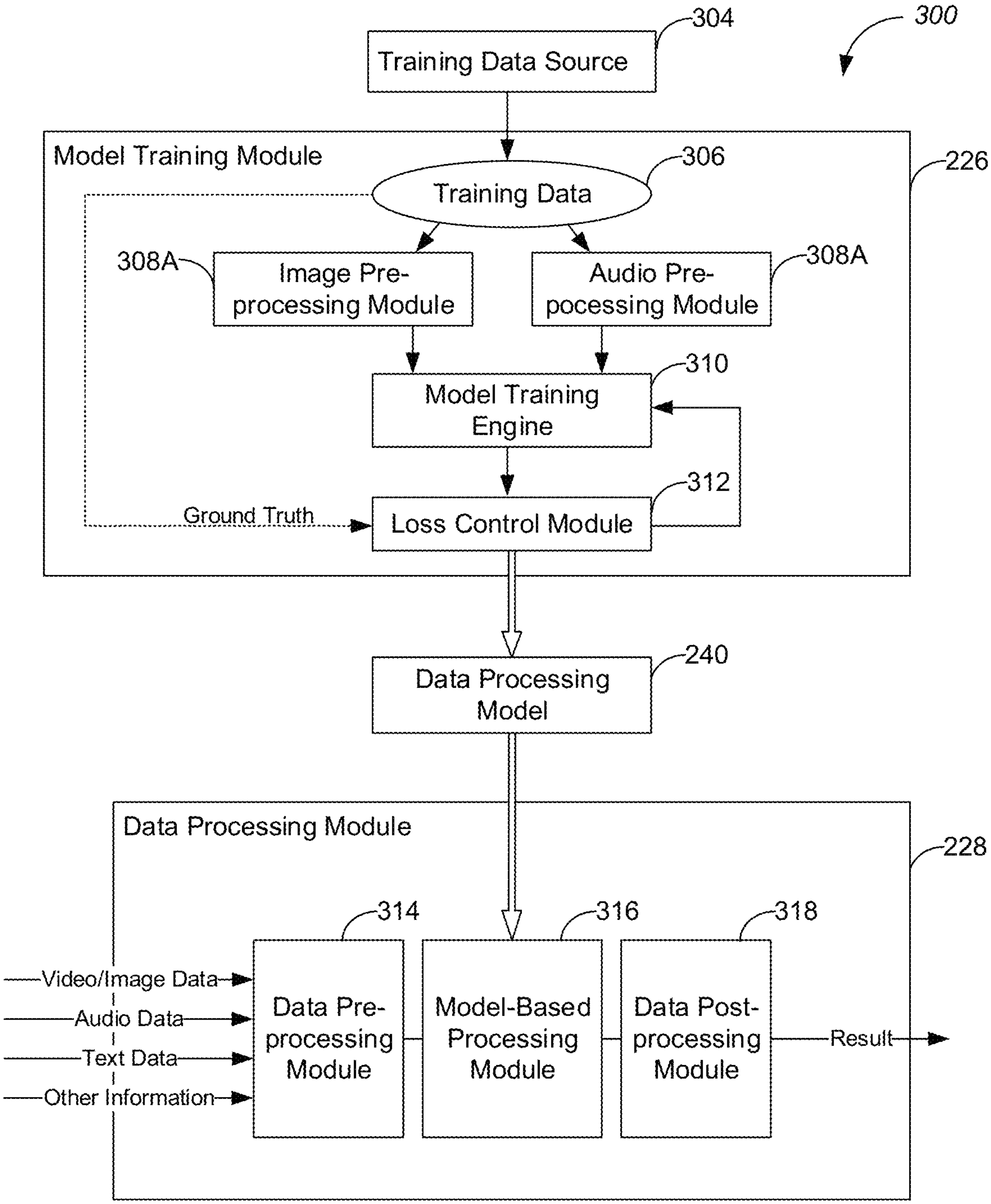

300
304
Training Data Source
Model Training Module
226
Training Data
306
308A
Image Pre-processing Module
Audio Pre-processing Module
308A
Model Training Engine
310
312
Ground Truth
Loss Control Module
Data Processing Model
240
Data Processing Module
228
314
316
318
Video/Image Data
Audio Data
Text Data
Other Information
Data Pre-processing Module
Model-Based Processing Module
Data Post-processing Module
Result

FIG 3

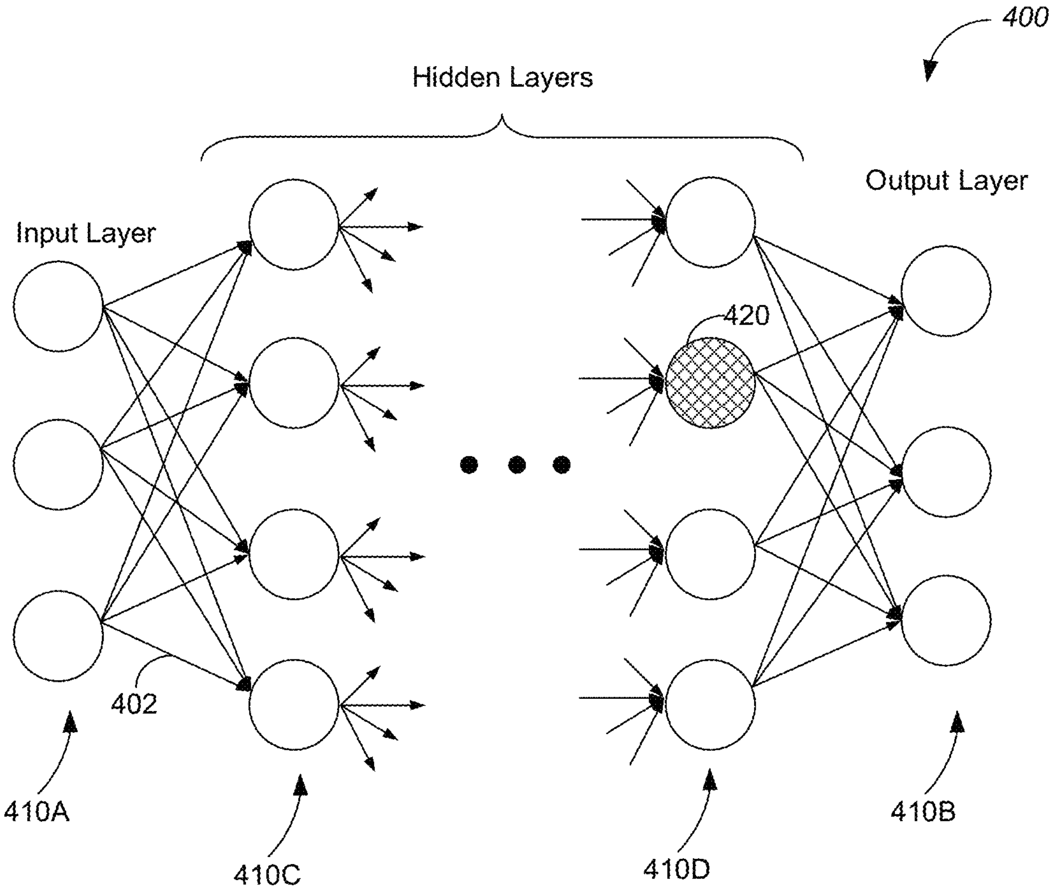

400
Hidden Layers
Input Layer
Output Layer
420
402
410A
410C
410D
410B

FIG 4A

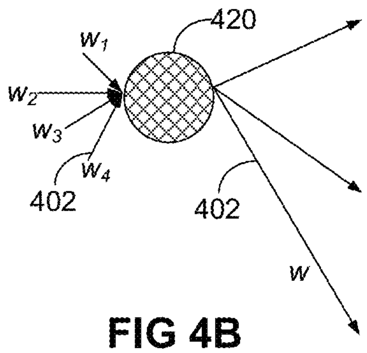

420
w_1
w_2
w_3
w_4
402
402
w

FIG 4B

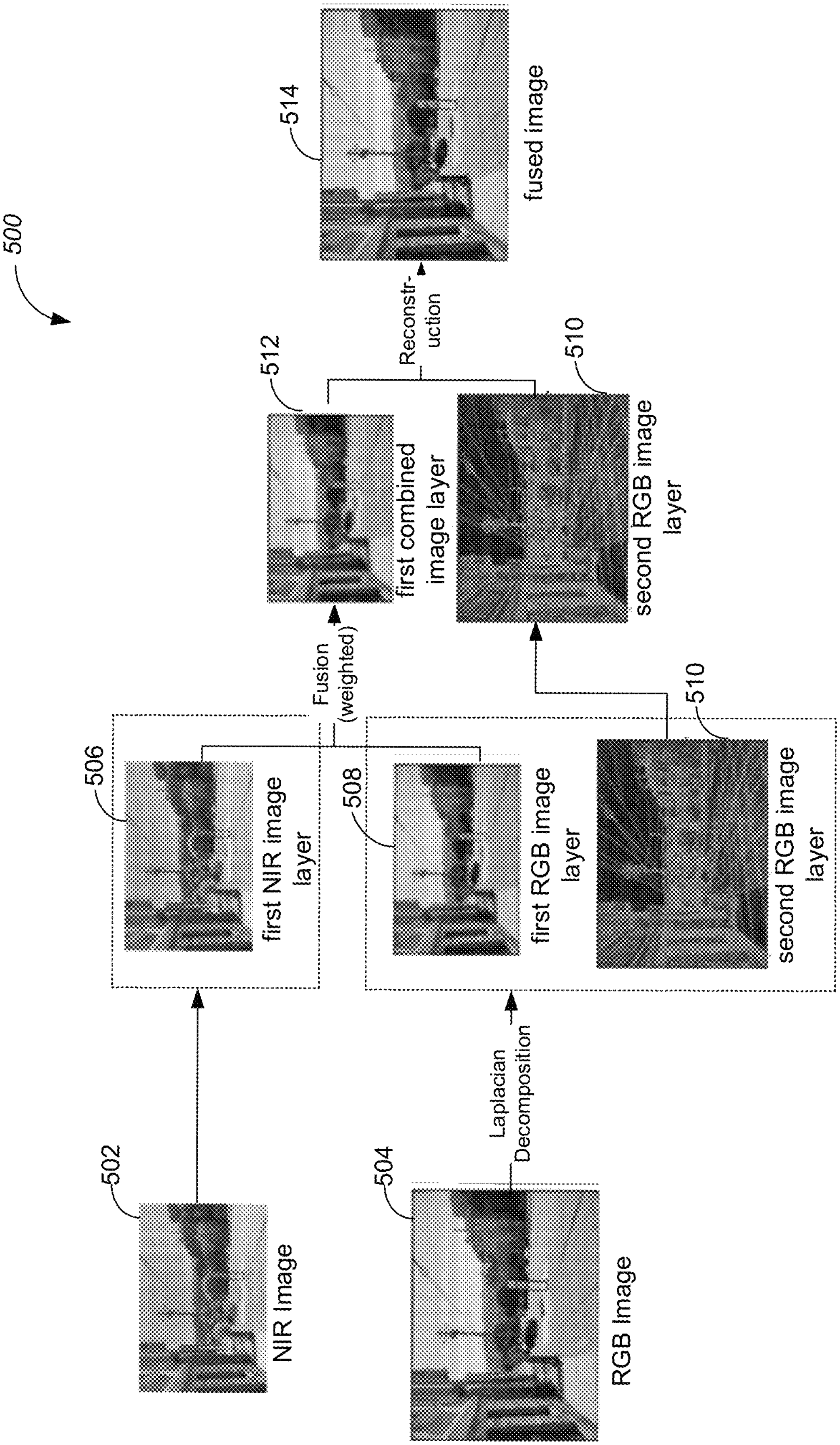

500
502
NIR Image
504
RGB Image
Laplacian Decomposition
506
first NIR image layer
508
first RGB image layer
510
second RGB image layer
Fusion (weighted)
512
first combined image layer
510
second RGB image layer
Reconstr-uction
514
fused image

FIG 5

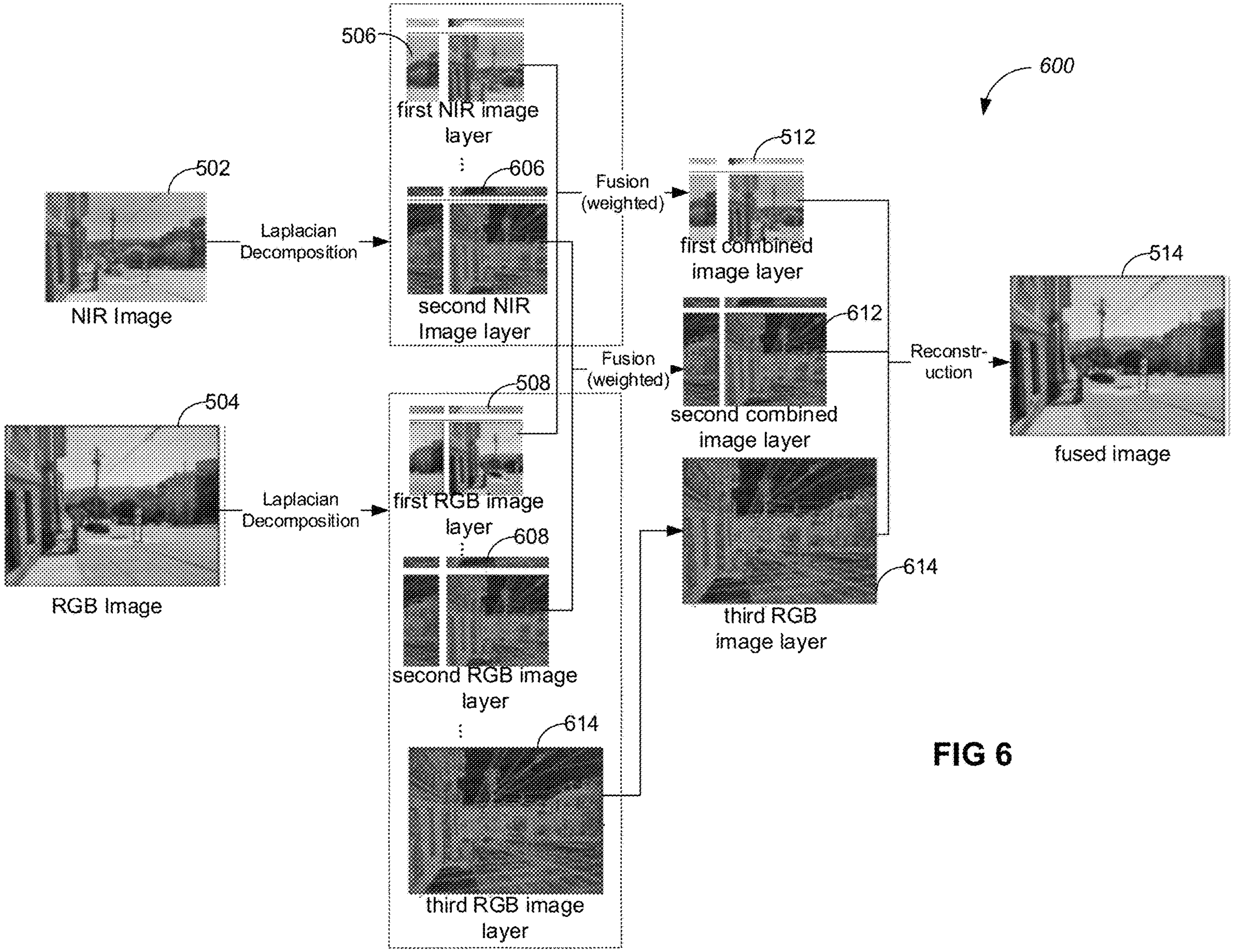

600
502
NIR Image
504
RGB Image
Laplacian Decomposition
Laplacian Decomposition
506
first NIR image layer
606
second NIR Image layer
508
first RGB image layer
608
second RGB image layer
614
third RGB image layer
Fusion (weighted)
Fusion (weighted)
512
first combined image layer
612
second combined image layer
614
third RGB image layer
Reconstr-uction
514
fused image

FIG 6

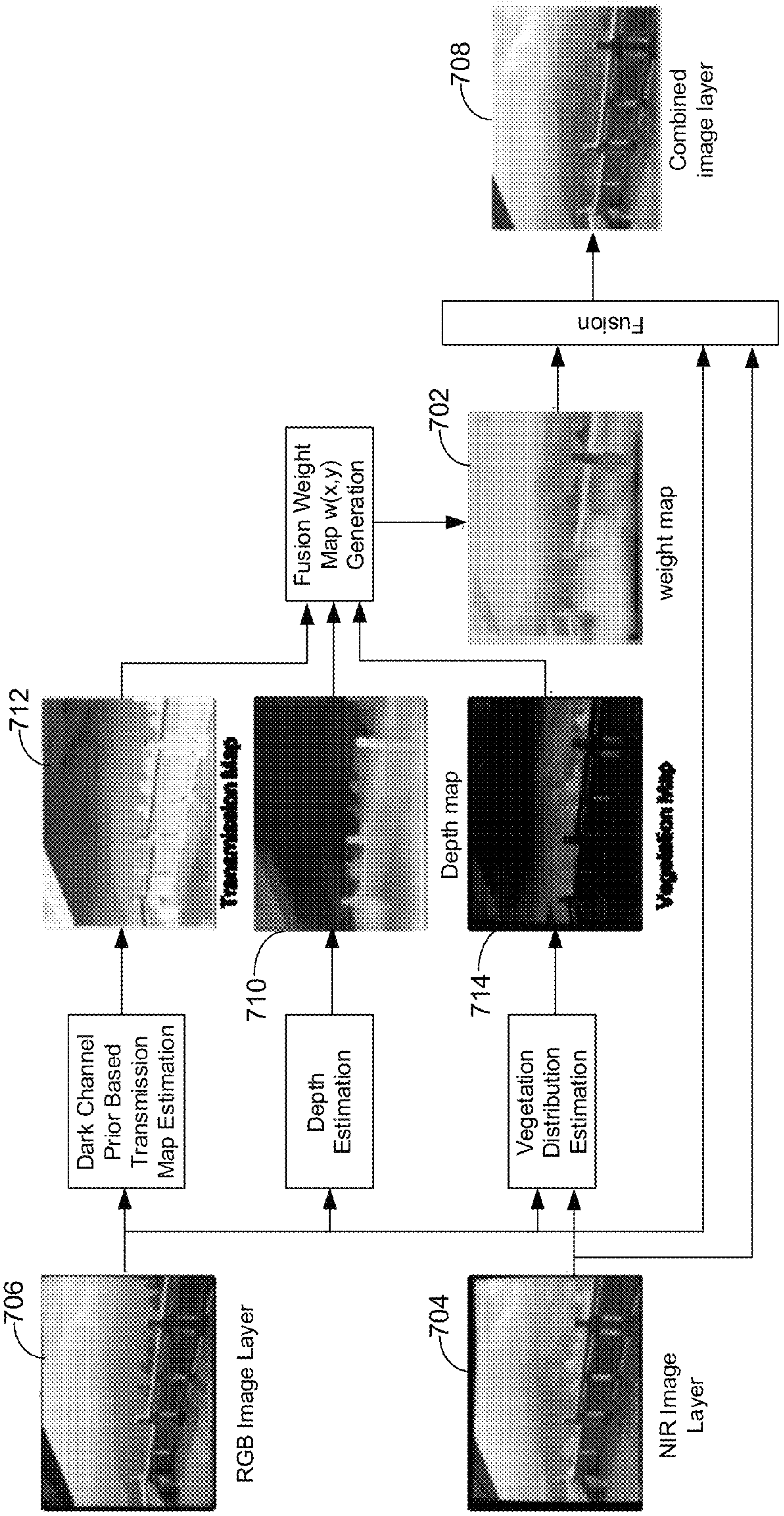
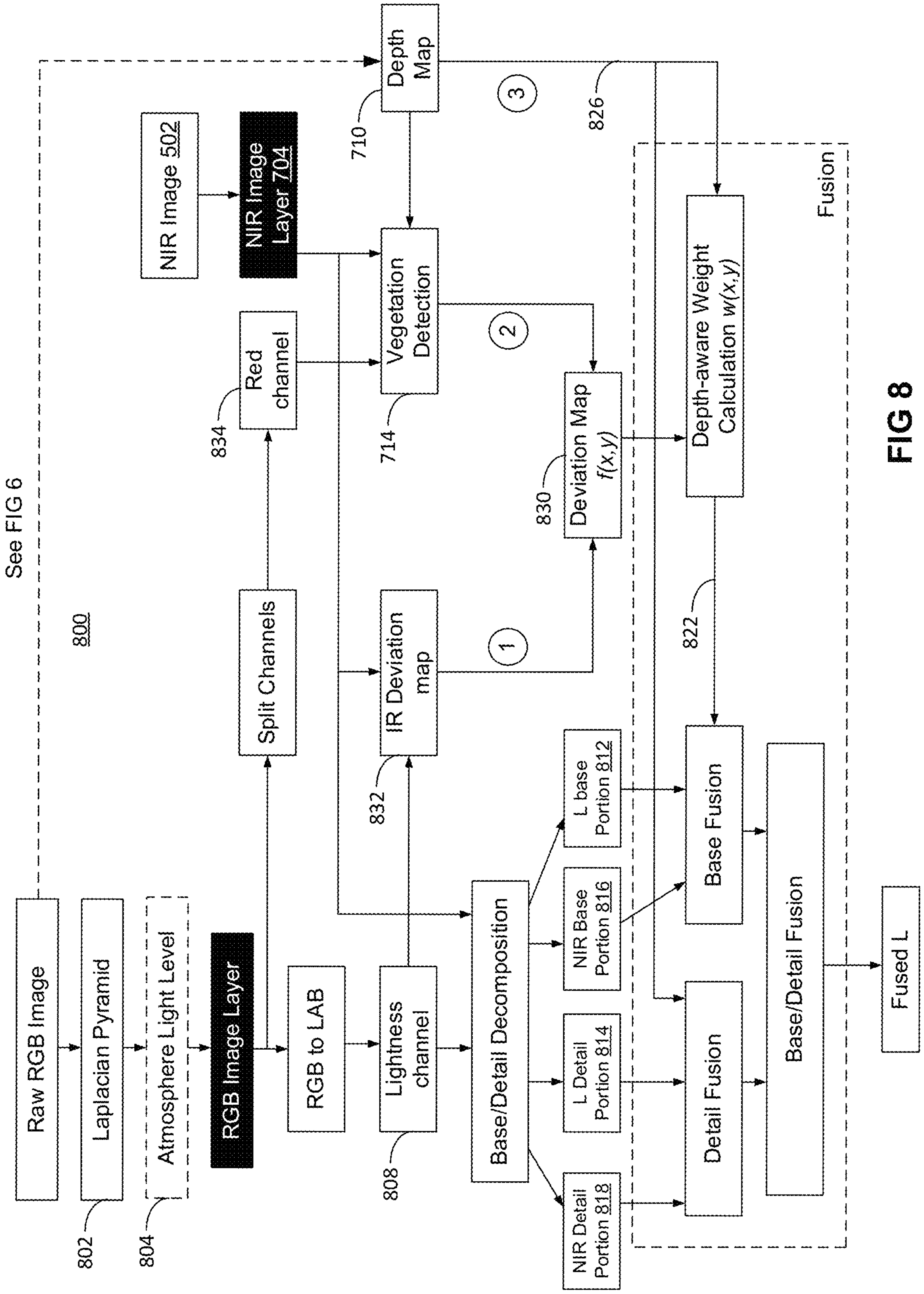

706
RGB Image Layer
704
NIR Image Layer
Dark Channel Prior Based Transmission Map Estimation
Depth Estimation
Vegetation Distribution Estimation
712
Transmission Map
710
Depth map
714
Vegetation Map
Fusion Weight Map w(x,y) Generation
702
weight map
Fusion
708
Combined image layer

FIG 7



800
See FIG 6
Raw RGB Image
Laplacian Pyramid
802
Atmosphere Light Level
804
RGB Image Layer
RGB to LAB
Lightness channel
808
Split Channels
Red channel
834
Base/Detail Decomposition
IR Deviation map
832
NIR Image 502
NIR Image Layer 704
Vegetation Detection
714
Depth Map
710
1
2
3
Deviation Map f(x,y)
830
826
L base Portion 812
NIR Base Portion 816
L Detail Portion 814
NIR Detail Portion 818
Fusion
Depth-aware Weight Calculation w(x,y)
822
Base Fusion
Detail Fusion
Base/Detail Fusion
Fused L

FIG 8

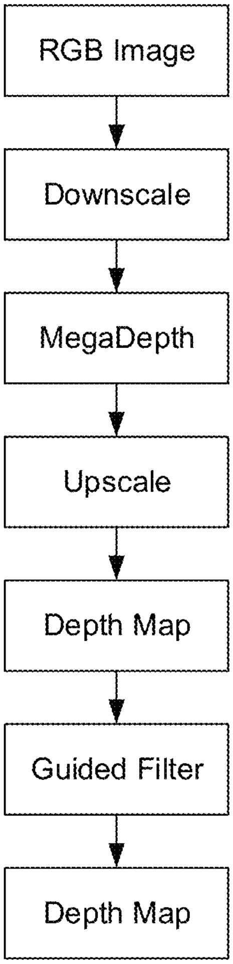

RGB Image
Downscale
MegaDepth
Upscale
Depth Map
Guided Filter
Depth Map

FIG 9

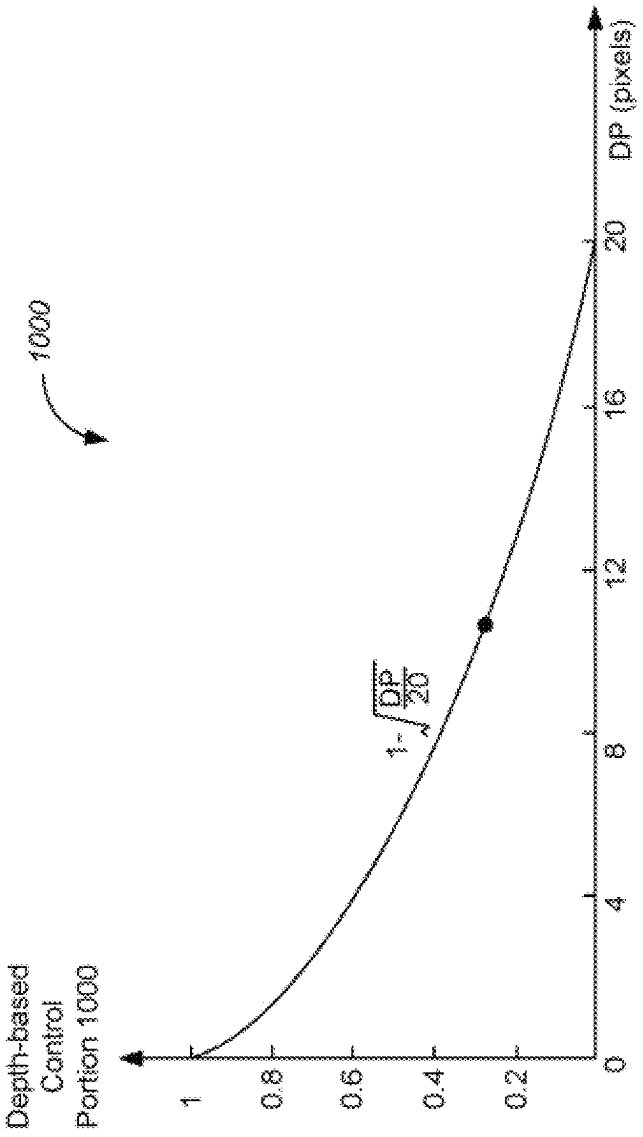

1000
Depth-based Control Portion 1000
1
0.8
0.6
0.4
0.2
0
4
8
12
16
20
DP (pixels)
$1-\sqrt{\frac{DP}{20}}$

Figure 10

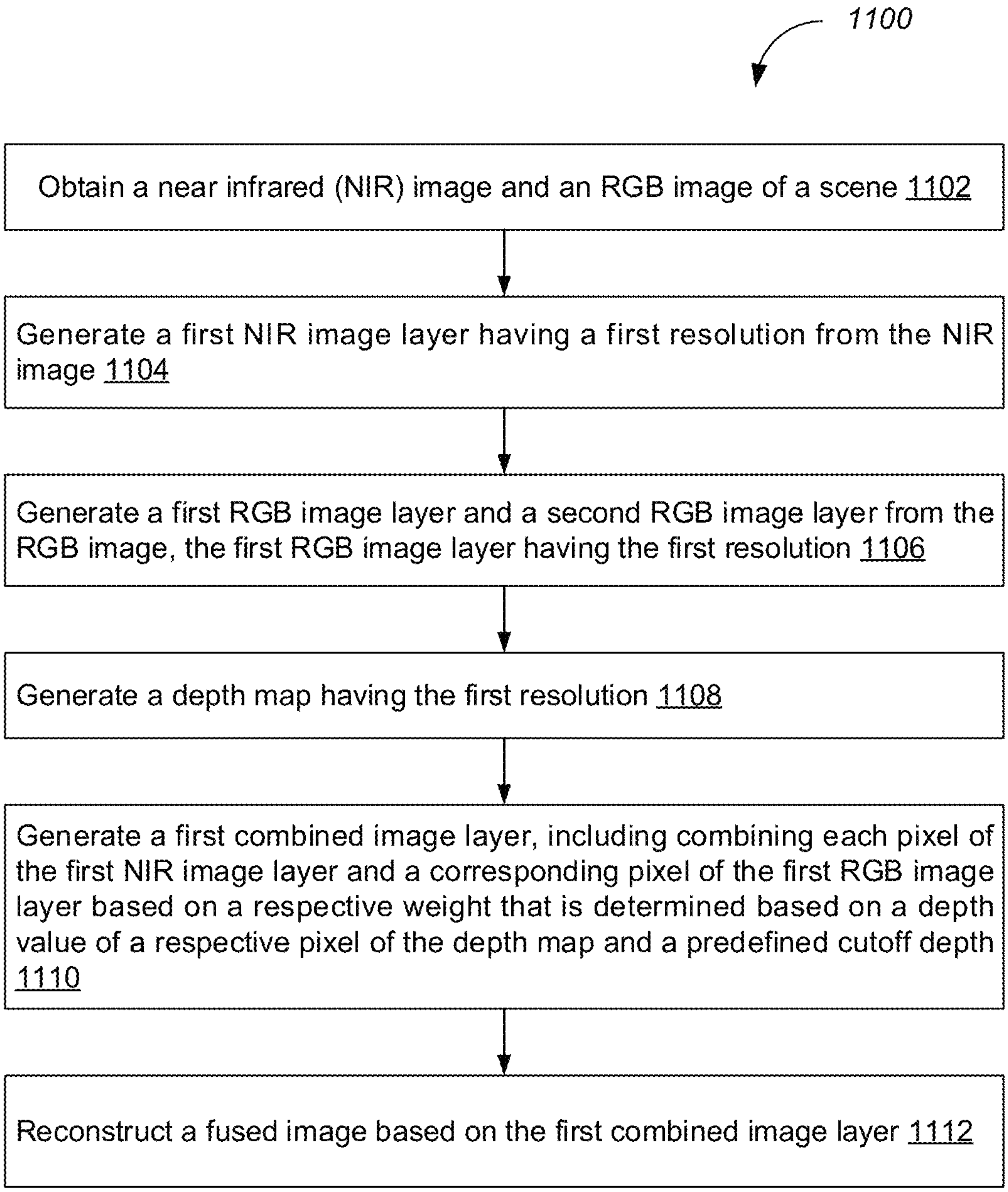

1100
Obtain a near infrared (NIR) image and an RGB image of a scene 1102
Generate a first NIR image layer having a first resolution from the NIR image 1104
Generate a first RGB image layer and a second RGB image layer from the RGB image, the first RGB image layer having the first resolution 1106
Generate a depth map having the first resolution 1108
Generate a first combined image layer, including combining each pixel of the first NIR image layer and a corresponding pixel of the first RGB image layer based on a respective weight that is determined based on a depth value of a respective pixel of the depth map and a predefined cutoff depth 1110
Reconstruct a fused image based on the first combined image layer 1112

FIG 11

DEPTH-BASED SEE-THROUGH PREVENTION IN IMAGE FUSION

RELATED APPLICATIONS

This disclosure is a continuation of International Application No. PCT/US2021/021379, filed Mar. 8, 2021, which claims priority to U.S. Provisional Patent Application No. 63/113,168, filed Nov. 12, 2020, and U.S. Provisional Patent Application No. 63/113,624, filed Nov. 13, 2020, the entire disclosures of the above-mentioned applications are incorporated herein by reference.

TECHNICAL FILED

The present disclosure generally relates to image processing, particularly to methods and systems for fusing images based on a depth map.

BACKGROUND

Image fusion techniques are applied to combine information from different image sources into a single image. Resulting images contain more information than that provided by any single image source. Different sensory modalities are often applied to provide different types of information (e.g., colors, brightness, and details) in an image fusion process. For example, color images are fused with near-infrared (NIR) images, which enhance details in the color images while preserving color and brightness information of the color images. Particularly, NIR light can travel through fog, smog, or haze better than visible light, allowing some dehazing algorithms to be established based on a combination of NIR and color images. However, some materials (e.g., some bottles and human clothes) that are opaque under visible light may appear transparent under the NIR light, thereby causing some privacy concerns and holding fusion of color and NIR images from being widely adopted in consumer electronic devices. Little work has been done to address this see-through issue in earlier image fusion work, and it would be beneficial to have a mechanism to suppress a see-through effect and address the privacy concerns in image fusion.

SUMMARY

The present disclosure describes embodiments related to combining information of a truecolor image (also called an RGB image) and a corresponding NIR image based on a depth map. A severity of a see-through effect depends on materials of objects exposed to NIR light, and the materials are difficult to recognize using computer vision. It is observed that the see-through effect is more prominent in close-up image shots of an object and becomes less significant as the object moves further away in a field of view. Based on such an observation, depth information is applied to assign fusion weights (e.g., reduce fusion weights for closeup objects), thereby suppressing the see-through effect effectively.

In one aspect, an image fusion method is implemented at a computer system (e.g., a server, an electronic device having a camera, or both of them) having one or more processors, memory. The method includes obtaining an NIR image and an RGB image of a scene, generating from the NIR image a first NIR image layer having a first resolution, generating from the RGB image a first RGB image layer and a second RGB image layer, and generating a depth map. Both the first RGB image layer and the depth image have the first resolution. The method further includes generating a first combined image layer by combining each pixel of the first NIR image layer and a corresponding pixel of the first RGB image layer based on a respective weight that is determined based on a depth value of a respective pixel of the depth map and a predefined cutoff depth. The method further includes reconstructing a fused image based on the first combined image layer.

In some embodiments, the second RGB image layer has a second resolution greater than the first resolution, and the depth map includes a first depth map. The method further includes generating from the NIR image a second NIR image layer having the second resolution, generating a second depth map having the second resolution, and generating a second combined image layer. Generating the second combined image layer further includes combining each pixel of the second NIR image layer and a corresponding pixel of the second RGB image layer based on a respective weight that is determined based on a depth value of a respective pixel of the second depth map and the predefined cutoff depth. The fused image is reconstructed from the first combined image layer and the second combined image layer.

According to another aspect of the present disclosure, a computer system includes one or more processing units, memory, and a plurality of programs stored in the memory. The programs, when executed by the one or more processing units, cause the one or more processing units to perform the method for fusing NIR and color images as described above.

According to another aspect of the present disclosure, a non-transitory computer readable storage medium stores a plurality of programs for execution by a computer system having one or more processing units. The programs, when executed by the one or more processing units, cause the one or more processing units to perform the method for fusing NIR and color images as described above.

BRIEF DESCRIPTION OF DRAWINGS

The accompanying drawings, which are included to provide a further understanding of the embodiments and are incorporated herein and constitute a part of the specification, illustrate the described embodiments and together with the description serve to explain the underlying principles.

FIG. **1** is an example data processing environment having one or more servers communicatively coupled to one or more client devices, in accordance with some embodiments.

FIG. **2** is a block diagram illustrating a data processing system, in accordance with some embodiments.

FIG. **3** is an example data processing environment for training and applying a neural network based (NN-based) data processing model for processing visual and/or audio data, in accordance with some embodiments.

FIG. **4**A is an example neural network applied to process content data in an NN-based data processing model, in accordance with some embodiments, and FIG. **4**B is an example node in the neural network, in accordance with some embodiments.

FIG. **5** is an example pyramid framework for fusing an NIR image and an RGB image, in accordance with some embodiments.

FIG. **6** is another example pyramid framework fusing an NIR image and an RGB image, in accordance with some embodiments.

FIG. **7** illustrates an example process of generating a weight map for fusing an NIR image and an RGB image, in accordance with some embodiments.

FIG. **8** is a flowchart of an overall process of fusing an NIR image and an RGB image using a depth-based weight map, in accordance with some embodiments.

FIG. **9** is a flowchart of a process of generating a depth map based on an RGB image, in accordance with some embodiments.

FIG. **10** is a diagram illustrating a depth-based control portion of an example weight assigning function, in accordance with some embodiments.

FIG. **11** is a flow diagram of an image fusion method implemented at a computer system, in accordance with some embodiments.

Like reference numerals refer to corresponding parts throughout the several views of the drawings.

DETAILED DESCRIPTION

Reference will now be made in detail to specific embodiments, examples of which are illustrated in the accompanying drawings. In the following detailed description, numerous non-limiting specific details are set forth in order to assist in understanding the subject matter presented herein. But it will be apparent to one of ordinary skill in the art that various alternatives may be used without departing from the scope of claims and the subject matter may be practiced without these specific details. For example, it will be apparent to one of ordinary skill in the art that the subject matter presented herein can be implemented on many types of electronic devices with digital video capabilities.

The present disclosure describes embodiments related to combining information of an RGB image and a corresponding NIR image based on a depth map. It is observed that the see-through effect is more prominent in close-up image shots of an object and becomes less significant as the object moves further away in a field of view. Based on such an observation, some implementations of this disclosure rely on a pyramid approach that separates different resolution levels of each related RGB or NIR image and combines the corresponding resolution levels of related RGB and NIR images selectively, thereby suppressing the see-through effect in one or more selected resolution levels. Specifically, depth information is applied to assign fusion weights (e.g., reduce fusion weights for closeup objects) to eliminate the see-through effect effectively. Such depth information can be estimated using different methods (e.g., Stereo, deep learning) and represented in different forms (e.g., absolute depth, disparity). In some situations, a focus point distance, an absolute depth, or normalized depth information is provided as an input according to predefined fusion rules. Such fusion rules are based on a depth map and can effectively block NIR information related to objects in a close range while keeping a desired fusion weight for NIR information for background regions.

FIG. **1** is an example data processing environment **100** having one or more servers **102** communicatively coupled to one or more client devices **104**, in accordance with some embodiments. The one or more client devices **104** may be, for example, desktop computers **104**A, tablet computers **104**B, mobile phones **104**C, or intelligent, multi-sensing, network-connected home devices (e.g., a surveillance camera **104**D). Each client device **104** can collect data or user inputs, executes user applications, or present outputs on its user interface. The collected data or user inputs can be processed locally at the client device **104** and/or remotely by the server(s) **102**. The one or more servers **102** provide system data (e.g., boot files, operating system images, and user applications) to the client devices **104**, and in some embodiments, processes the data and user inputs received from the client device(s) **104** when the user applications are executed on the client devices **104**. In some embodiments, the data processing environment **100** further includes a storage **106** for storing data related to the servers **102**, client devices **104**, and applications executed on the client devices **104**.

The one or more servers **102** can enable real-time data communication with the client devices **104** that are remote from each other or from the one or more servers **102**. In some embodiments, the one or more servers **102** can implement data processing tasks that cannot be or are preferably not completed locally by the client devices **104**. For example, the client devices **104** include a game console that executes an interactive online gaming application. The game console receives a user instruction and sends it to a game server **102** with user data. The game server **102** generates a stream of video data based on the user instruction and user data and providing the stream of video data for concurrent display on the game console and other client devices that are engaged in the same game session with the game console. In another example, the client devices **104** include a mobile phone **104**C and a networked surveillance camera **104**D. The camera **104**D collects video data and streams the video data to a surveillance camera server **102** in real time. While the video data is optionally pre-processed on the camera **104**D, the surveillance camera server **102** processes the video data to identify motion or audio events in the video data and share information of these events with the mobile phone **104**C, thereby allowing a user of the mobile phone **104**C to monitor the events occurring near the networked surveillance camera **104**D in real time and remotely.

The one or more servers **102**, one or more client devices **104**, and storage **106** are communicatively coupled to each other via one or more communication networks **108**, which are the medium used to provide communications links between these devices and computers connected together within the data processing environment **100**. The one or more communication networks **108** may include connections, such as wire, wireless communication links, or fiber optic cables. Examples of the one or more communication networks **108** include local area networks (LAN), wide area networks (WAN) such as the Internet, or a combination thereof. The one or more communication networks **108** are, optionally, implemented using any known network protocol, including various wired or wireless protocols, such as Ethernet, Universal Serial Bus (USB), FIREWIRE, Long Term Evolution (LTE), Global System for Mobile Communications (GSM), Enhanced Data GSM Environment (EDGE), code division multiple access (CDMA), time division multiple access (TDMA), Bluetooth, Wi-Fi, voice over Internet Protocol (VoIP), Wi-MAX, or any other suitable communication protocol. A connection to the one or more communication networks **108** may be established either directly (e.g., using 3G/4G connectivity to a wireless carrier), or through a network interface **110** (e.g., a router, switch, gateway, hub, or an intelligent, dedicated whole-home control node), or through any combination thereof. As such, the one or more communication networks **108** can represent the Internet of a worldwide collection of networks and gateways that use the Transmission Control Protocol/Internet Protocol (TCP/IP) suite of protocols to communicate with one another. At the heart of the Internet is a backbone of high-speed data communication lines between major nodes or host computers, consisting of thousands of commercial, governmental, educational and other computer systems that route data and messages.

In some embodiments, deep learning techniques are applied in the data processing environment **100** to process content data (e.g., video, image, audio, or textual data) obtained by an application executed at a client device **104** to identify information contained in the content data, match the content data with other data, categorize the content data, or synthesize related content data. In these deep learning techniques, data processing models are created based on one or more neural networks to process the content data. These data processing models are trained with training data before they are applied to process the content data. In some embodiments, both model training and data processing are implemented locally at each individual client device **104** (e.g., the client device **104**C). The client device **104**C obtains the training data from the one or more servers **102** or storage **106** and applies the training data to train the data processing models. Subsequently to model training, the client device **104**C obtains the content data (e.g., captures video data via an internal camera) and processes the content data using the training data processing models locally. Alternatively, in some embodiments, both model training and data processing are implemented remotely at a server **102** (e.g., the server **102**A) associated with one or more client devices **104** (e.g., the client devices **104**A and **104**D). The server **102**A obtains the training data from itself, another server **102** or the storage **106** and applies the training data to train the data processing models. The client device **104**A or **104**D obtains the content data and sends the content data to the server **102**A (e.g., in a user application) for data processing using the trained data processing models. The same client device or a distinct client device **104**A receives data processing results from the server **102**A, and presents the results on a user interface (e.g., associated with the user application). The client device **104**A or **104**D itself implements no or little data processing on the content data prior to sending them to the server **102**A. Additionally, in some embodiments, data processing is implemented locally at a client device **104** (e.g., the client device **104**B), while model training is implemented remotely at a server **102** (e.g., the server **102**B) associated with the client device **104**B. The server **102**B obtains the training data from itself, another server **102** or the storage **106** and applies the training data to train the data processing models. The trained data processing models are optionally stored in the server **102**B or storage **106**. The client device **104**B imports the trained data processing models from the server **102**B or storage **106**, processes the content data using the data processing models, and generates data processing results to be presented on a user interface locally.

In various embodiments of this disclosure, distinct images are captured by a camera (e.g., a standalone surveillance camera **104**D or an integrated camera of a client device **104**A), and processed in the same camera, the client device **104**A containing the camera, a server **102**, or a distinct client device **104**. Optionally, deep learning techniques are trained or applied for the purposes of processing the images. In an example, a near infrared (NIR) image and an RGB image are captured by the camera. After obtaining the NIR and RGB image, the same camera, client device **104**A containing the camera, server **102**, or distinct client device **104** extracts a first NIR image layer and a first RGB image layer from the NIR image and the RGB image, respectively, and generates a depth map. The first NIR and RGB image layers and depth image share the same resolution. Each pixel of the first NIR image layer and a corresponding pixel of the first RGB image layer are combined based on a respective weight that is determined based on a depth value of a respective pixel of the depth map and a predefined cutoff depth. Such a combined image layer selectively suppresses details offered by the NIR image, thereby avoiding a see-through effect commonly seen in many detailed images. The combined image layer is used to reconstruct a color image that can be reviewed on the client device **104**A containing the camera or the distinct client device **104**.

FIG. **2** is a block diagram illustrating a data processing system **200**, in accordance with some embodiments. The data processing system **200** includes a server **102**, a client device **104**, a storage **106**, or a combination thereof. The data processing system **200**, typically, includes one or more processing units (CPUs) **202**, one or more network interfaces **204**, memory **206**, and one or more communication buses **208** for interconnecting these components (sometimes called a chipset). The data processing system **200** includes one or more input devices **210** that facilitate user input, such as a keyboard, a mouse, a voice-command input unit or microphone, a touch screen display, a touch-sensitive input pad, a gesture capturing camera, or other input buttons or controls. Furthermore, in some embodiments, the client device **104** of the data processing system **200** uses a microphone and voice recognition or a camera and gesture recognition to supplement or replace the keyboard. In some embodiments, the client device **104** includes one or more cameras, scanners, or photo sensor units for capturing images, for example, of graphic serial codes printed on the electronic devices. The data processing system **200** also includes one or more output devices **212** that enable presentation of user interfaces and display content, including one or more speakers and/or one or more visual displays. Optionally, the client device **104** includes a location detection device, such as a GPS (global positioning satellite) or other geo-location receiver, for determining the location of the client device **104**.

Memory **206** includes high-speed random access memory, such as DRAM, SRAM, DDR RAM, or other random access solid state memory devices; and, optionally, includes non-volatile memory, such as one or more magnetic disk storage devices, one or more optical disk storage devices, one or more flash memory devices, or one or more other non-volatile solid state storage devices. Memory **206**, optionally, includes one or more storage devices remotely located from one or more processing units **202**. Memory **206**, or alternatively the non-volatile memory within memory **206**, includes a non-transitory computer readable storage medium. In some embodiments, memory **206**, or the non-transitory computer readable storage medium of memory **206**, stores the following programs, modules, and data structures, or a subset or superset thereof:

Operating system **214** including procedures for handling various basic system services and for performing hardware dependent tasks;

Network communication module **216** for connecting each server **102** or client device **104** to other devices (e.g., server **102**, client device **104**, or storage **106**) via one or more network interfaces **204** (wired or wireless) and one or more communication networks **108**, such as the Internet, other wide area networks, local area networks, metropolitan area networks, and so on;

User interface module **218** for enabling presentation of information (e.g., a graphical user interface for application(s) **224**, widgets, websites and web pages thereof, and/or games, audio and/or video content, text, etc.) at each client device **104** via one or more output devices **212** (e.g., displays, speakers, etc.);

Input processing module **220** for detecting one or more user inputs or interactions from one of the one or more input devices **210** and interpreting the detected input or interaction;

Web browser module **222** for navigating, requesting (e.g., via HTTP), and displaying websites and web pages thereof, including a web interface for logging into a user account associated with a client device **104** or another electronic device, controlling the client or electronic device if associated with the user account, and editing and reviewing settings and data that are associated with the user account;

One or more user applications **224** for execution by the data processing system **200** (e.g., games, social network applications, smart home applications, and/or other web or non-web based applications for controlling another electronic device and reviewing data captured by such devices);

Model training module **226** for receiving training data and establishing a data processing model for processing content data (e.g., video, image, audio, or textual data) to be collected or obtained by a client device **104**;

Data processing module **228** for processing content data using data processing models **240**, thereby identifying information contained in the content data, matching the content data with other data, categorizing the content data, or synthesizing related content data, where in some embodiments, the data processing module **228** is associated with one of the user applications **224** to process the content data in response to a user instruction received from the user application **224**;

Depth-based image processing module **250** for decomposing each of different types of images (e.g., an NIR image and an RGB image) to one or more respective image layers, combining two associated image layers decomposed from two different types of images based on a depth map, and reconstructing an image based on a combined image layer, where in some embodiments, one or more image processing operations involve deep learning and are implemented jointly with the data processing module **228**; and

One or more databases **230** for storing at least data including one or more of:

Device settings **232** including common device settings (e.g., service tier, device model, storage capacity, processing capabilities, communication capabilities, etc.) of the one or more servers **102** or client devices **104**;

User account information **234** for the one or more user applications **224**, e.g., user names, security questions, account history data, user preferences, and predefined account settings;

Network parameters **236** for the one or more communication networks **108**, e.g., IP address, subnet mask, default gateway, DNS server and hostname;

Training data **238** for training one or more data processing models **240**;

Data processing model(s) **240** for processing content data (e.g., video, image, audio, or textual data) using deep learning techniques; and

Content data and results **242** that are obtained by and outputted to the client device **104** of the data processing system **200**, respectively, where the content data is processed locally at a client device **104** or remotely at a server **102** or a distinct client device **104** to provide the associated results **242** to be presented on the same or distinct client device **104**, and examples of the content data and results **242** include RGB images, NIR images, depth maps, and images reconstructed therefrom.

Optionally, the one or more databases **230** are stored in one of the server **102**, client device **104**, and storage **106** of the data processing system **200**. Optionally, the one or more databases **230** are distributed in more than one of the server **102**, client device **104**, and storage **106** of the data processing system **200**. In some embodiments, more than one copy of the above data is stored at distinct devices, e.g., two copies of the data processing models **240** are stored at the server **102** and storage **106**, respectively.

Each of the above identified elements may be stored in one or more of the previously mentioned memory devices, and corresponds to a set of instructions for performing a function described above. The above identified modules or programs (i.e., sets of instructions) need not be implemented as separate software programs, procedures, modules or data structures, and thus various subsets of these modules may be combined or otherwise re-arranged in various embodiments. In some embodiments, memory **206**, optionally, stores a subset of the modules and data structures identified above. Furthermore, memory **206**, optionally, stores additional modules and data structures not described above.

FIG. **3** is another example data processing system **300** for training and applying a neural network based (NN-based) data processing model **240** for processing content data (e.g., video, image, audio, or textual data), in accordance with some embodiments. The data processing system **300** includes a model training module **226** for establishing the data processing model **240** and a data processing module **228** for processing the content data using the data processing model **240**. In some embodiments, both of the model training module **226** and the data processing module **228** are located on a client device **104** of the data processing system **300**, while a training data source **304** distinct from the client device **104** provides training data **306** to the client device **104**. The training data source **304** is optionally a server **102** or storage **106**. Alternatively, in some embodiments, both of the model training module **226** and the data processing module **228** are located on a server **102** of the data processing system **300**. The training data source **304** providing the training data **306** is optionally the server **102** itself, another server **102**, or the storage **106**. Additionally, in some embodiments, the model training module **226** and the data processing module **228** are separately located on a server **102** and client device **104**, and the server **102** provides the trained data processing model **240** to the client device **104**.

The model training module **226** includes one or more data pre-processing modules **308**, a model training engine **310**, and a loss control module **312**. The data processing model **240** is trained according to a type of the content data to be processed. The training data **306** is consistent with the type of the content data, so a data pre-processing module **308** applied to process the training data **306** is consistent with the type of the content data. For example, an image pre-processing module **308**A is configured to process image training data **306** to a predefined image format, e.g., extract a region of interest (ROI) in each training image, and crop each training image to a predefined image size. Alternatively, an audio pre-processing module **308**B is configured to process audio training data **306** to a predefined audio format, e.g., converting each training sequence to a frequency domain using a Fourier transform. The model training engine **310** receives pre-processed training data provided by the data pre-processing modules **308**, further processes the pre-processed training data using an existing data processing model **240**, and generates an output from each training data item. During this course, the loss control module **312** can monitor a loss function comparing the output associated with the respective training data item and a ground truth of the respective training data item. The model training engine **310** modifies the data processing model **240** to reduce the loss function, until the loss function satisfies a loss criteria (e.g., a comparison result of the loss function is minimized or reduced below a loss threshold). The modified data processing model **240** is provided to the data processing module **228** to process the content data.

In some embodiments, the model training module **226** offers supervised learning in which the training data is entirely labelled and includes a desired output for each training data item (also called the ground truth in some situations). Conversely, in some embodiments, the model training module **226** offers unsupervised learning in which the training data are not labelled. The model training module **226** is configured to identify previously undetected patterns in the training data without pre-existing labels and with no or little human supervision. Additionally, in some embodiments, the model training module **226** offers partially supervised learning in which the training data are partially labelled.

The data processing module **228** includes a data pre-processing modules **314**, a model-based processing module **316**, and a data post-processing module **318**. The data pre-processing modules **314** pre-processes the content data based on the type of the content data. Functions of the data pre-processing modules **314** are consistent with those of the pre-processing modules **308** and covert the content data to a predefined content format that is acceptable by inputs of the model-based processing module **316**. Examples of the content data include one or more of: video, image, audio, textual, and other types of data. For example, each image is pre-processed to extract an ROI or cropped to a predefined image size, and an audio clip is pre-processed to convert to a frequency domain using a Fourier transform. In some situations, the content data includes two or more types, e.g., video data and textual data. The model-based processing module **316** applies the trained data processing model **240** provided by the model training module **226** to process the pre-processed content data. The model-based processing module **316** can also monitor an error indicator to determine whether the content data has been properly processed in the data processing model **240**. In some embodiments, the processed content data is further processed by the data post-processing module **318** to present the processed content data in a preferred format or to provide other related information that can be derived from the processed content data.

FIG. **4**A is an example neural network (NN) **400** applied to process content data in an NN-based data processing model **240**, in accordance with some embodiments, and FIG. **4**B is an example node **420** in the neural network (NN) **400**, in accordance with some embodiments. The data processing model **240** is established based on the neural network **400**. A corresponding model-based processing module **316** applies the data processing model **240** including the neural network **400** to process content data that has been converted to a predefined content format. The neural network **400** includes a collection of nodes **420** that are connected by links **412**. Each node **420** receives one or more node inputs and applies a propagation function to generate anode output from the one or more node inputs. As the node output is provided via one or more links **412** to one or more other nodes **420**, a weight w associated with each link **412** is applied to the node output. Likewise, the one or more node inputs are combined based on corresponding weights w_1, w_2, w_3, and w_4 according to the propagation function. In an example, the propagation function is a product of a non-linear activation function and a linear weighted combination of the one or more node inputs.

The collection of nodes **420** is organized into one or more layers in the neural network **400**. Optionally, the one or more layers include a single layer acting as both an input layer and an output layer. Optionally, the one or more layers include an input layer **402** for receiving inputs, an output layer **406** for providing outputs, and zero or more hidden layers **404** (e.g., **404**A and **404**B) between the input and output layers **402** and **406**. A deep neural network has more than one hidden layers **404** between the input and output layers **402** and **406**. In the neural network **400**, each layer is only connected with its immediately preceding and/or immediately following layer. In some embodiments, a layer **402** or **404**B is a fully connected layer because each node **420** in the layer **402** or **404**B is connected to every node **420** in its immediately following layer. In some embodiments, one of the one or more hidden layers **404** includes two or more nodes that are connected to the same node in its immediately following layer for down sampling or pooling the nodes **420** between these two layers. Particularly, max pooling uses a maximum value of the two or more nodes in the layer **404**B for generating the node of the immediately following layer **406** connected to the two or more nodes.

In some embodiments, a convolutional neural network (CNN) is applied in a data processing model **240** to process content data (particularly, video and image data). The CNN employs convolution operations and belongs to a class of deep neural networks **400**, i.e., a feedforward neural network that only moves data forward from the input layer **402** through the hidden layers to the output layer **406**. The one or more hidden layers of the CNN are convolutional layers convolving with a multiplication or dot product. Each node in a convolutional layer receives inputs from a receptive area associated with a previous layer (e.g., five nodes), and the receptive area is smaller than the entire previous layer and may vary based on a location of the convolution layer in the convolutional neural network. Video or image data is pre-processed to a predefined video/image format corresponding to the inputs of the CNN. The pre-processed video or image data is abstracted by each layer of the CNN to a respective feature map. By these means, video and image data can be processed by the CNN for video and image recognition, classification, analysis, imprinting, or synthesis.

Alternatively and additionally, in some embodiments, a recurrent neural network (RNN) is applied in the data processing model **240** to process content data (particularly, textual and audio data). Nodes in successive layers of the RNN follow a temporal sequence, such that the RNN exhibits a temporal dynamic behavior. In an example, each node **420** of the RNN has a time-varying real-valued activation. Examples of the RNN include, but are not limited to, a long short-term memory (LSTM) network, a fully recurrent network, an Elman network, a Jordan network, a Hopfield network, a bidirectional associative memory (BAM) network, an echo state network, an independently RNN (IndRNN), a recursive neural network, and a neural history compressor. In some embodiments, the RNN can be used for handwriting or speech recognition. It is noted that in some embodiments, two or more types of content data are processed by the data processing module **228**, and two or more types of neural networks (e.g., both CNN and RNN) are applied to process the content data jointly.

The training process is a process for calibrating all of the weights w_i for each layer of the learning model using a training data set which is provided in the input layer **402**. The training process typically includes two steps, forward propagation and backward propagation, which are repeated multiple times until a predefined convergence condition is satisfied. In the forward propagation, the set of weights for different layers are applied to the input data and intermediate results from the previous layers. In the backward propagation, a margin of error of the output (e.g., a loss function) is measured, and the weights are adjusted accordingly to decrease the error. The activation function is optionally linear, rectified linear unit, sigmoid, hyperbolic tangent, or of other types. In some embodiments, a network bias term b is added to the sum of the weighted outputs from the previous layer before the activation function is applied. The network bias b provides a perturbation that helps the NN **400** avoid over fitting the training data. The result of the training includes the network bias parameter b for each layer.

FIG. **5** is an example pyramid framework **500** for fusing an NIR image **502** and an RGB image **504**, in accordance with some embodiments. The pyramid framework **500** is implemented at a computer system (e.g., a server **102**, a client device **104**, or a combination thereof). The computer system obtains the NIR image **502** and RGB image **504** of a scene. In some embodiments, the NIR image **502** and RGB image **504** are captured by a primary sensor and a secondary sensor of a client device (e.g., a surveillance camera **104**D), respectively. In some embodiments, each of the NIR and RGB images **502** and **504** is pre-processed, e.g., to reduce a distortion level of at least a portion of the RGB and NIR images, to implement an image registration process that transforms the NIR and RGB images **502** and **504** into a coordinate system associated with the scene. In an example, only one of the NIR and RGB images **502** and **504** is processed to match the other one of the NIR and RGB images **502** and **504**. The computer system configured to implement the pyramid framework **500** is optionally the camera **104**D itself, the client device containing a camera that captures the NIR and RGB images, the server **102**, a distinct client device configured to review a fusion output of the framework **500**, or any combination of them.

The RGB image **504** optionally has a resolution greater than that of the NIR image **502**. The computer system generates a first NIR image layer **506** from the NIR image **502**, and the first NIR image layer **506** has a first resolution. The computer system generates a first RGB image layer **508** and a second RGB image layer **510** from the RGB image **504**. The first RGB image layer **508** has the same resolution as the first NIR image layer **506**, and is therefore combined with the first NIR image layer **506** on a pixel-by-pixel basis to generate a first combined image layer **512**. Specifically, each pixel of the first RGB image layer **508** is combined with a corresponding pixel of the first NIR image layer **506** using a weight associated with the respective pixel. Each pixel of the resulting first combined image layer **512** (I_{COMB} (x, y)) is represented as follows:

$$I_{COMB}(x,y)=w(x,y)\times I_{NIR}(x,y)+(1-w(x,y))\times I_{RGB}(x,y) \quad (1)$$

where I_{RGB}(x,y) and I_{NIR}(x,y) are values of the respective pixel located at a position (x,y) in the first RGB image layer **508** and the first NIR image layer **506**, respectively, and w(x,y) is the respective weight associated with the first NIR image layer **506**. For each pixel, the respective weight w(x,y) is determined based on a depth value of the respective pixel of a depth map and a predefined cutoff depth D_{cutoff}. The depth map has the same resolution as the first RGB image layer **508** and the first NIR image layer **506**.

In some embodiments, an adaptive fusion rule is applied to associate the respective weight w(x,y) with each of different pixel locations, when the first NIR and RGB image layers **506** and **508** are combined. The respective weight w(x,y) of a pixel location (x,y) is expressed as a weigh assigning function of an image patch centered at the pixel location (x,y):

$$w(x,y)=f(I_{RGB}(i,j),I_{NIR}(i,j),i\in[x-\text{win},x+\text{win}],j\in[y-\text{win},\ y+\text{win}] \quad (2)$$

where the image patch includes pixels physically located within a two-dimensional range ±win of the pixel location (x,y), and f(I_{RGB}, I_{NIR}) is a weight peak value that is not modified directly by any depth value associated with the pixel location (x,y). In some embodiments, the weight peak value f(I_{RGB}, I_{NIR}) is based on one or more of a transmission level, a vegetation level and an infrared deviation level of the image patch. More details on the weight peak value f(I_{RGB}, I_{NIR}) are explained below with reference to FIGS. **7** and **8**.

In some embodiments, for the first NIR image layer **506**, an image patch centered at a specific pixel location (x,y) is associated with a visual feature (e.g., a human body, an object in a pocket, content of a document page), and preferred to be hidden from any review. A two-step depth based see-through prevention method is applied to suppress the image patch corresponding to the visual feature in the first NIR image layer **506** when the first NIR image layer **506** is combined with the first RGB image layer **508**. First, in some embodiments, camera focus statistics are used to filter out close-up shots that contains an object having a see-through issue. The NIR image **502** includes camera focus information that is recorded when the NIR image **502** is captured by a camera, e.g., in an auto-focus or manual scheme. For example, the camera focus information optionally includes a focal length that can be used as a reference to determine how far an object is from the camera. The NIR image **502** can be deleted or disabled from being used in any image fusion if the focal length indicates that the object is within an unsafe range that suffers from the see-through issue. Second, in some embodiments, a focal point of the NIR image **502** is beyond the unsafe range, i.e., the focal length is greater than a corresponding threshold. The depth map is used as a parameter in the weight assigning function as follows:

$$w(x,y)=f(I_{RGB}(i,j),I_{NIR}(i,j),D(i,j)),i\in[x-\text{win},x+\text{win}],j\in[y-\text{win},y+\text{win}] \quad (3)$$

where D(i,j) is an estimated scene depth value in a neighborhood of (x,y), i.e., the image patch centered at the pixel location (x,y).

In some embodiments, the scene depth D represents a true distance of an object from the camera. Given an absolute depth of the scene, the weight assigning function is represented as:

$$w(x,y)=f(I_{RGB}(i,j),I_{NIR}(i,j))*\min\left(1,\log_p\left(\max\left(1,\frac{D(x,y)}{D_{cutoff}}\right)\right)\right), \quad (4)$$
$$p\in(1,\infty]$$

where D_{cutoff} is a predefined cutoff depth beyond which the NIR image **502** is not capable of see through objects in the scene. In some embodiments, a value of the predefined cutoff depth D_{cutoff} is individualized for each individual camera and varies with lens specifications. The predefined cutoff depth D_{cutoff} can be measured.

Alternatively, in some embodiments, the image depth D of equations (2)-(4) corresponds to a disparity map of the scene, and each disparity value DP(x,y) in the disparity map is correlated with a reciprocal of an image depth D(x,y) given a baseline and camera parameters (e.g., a focal length) of the camera used to capture the RGB image **504**. Each disparity value is measured in pixels, e.g., equal to 20 or 30 pixels. In some situations, when camera information is limited and the absolute depth cannot be determined, the disparity map is applied to derive the weight assigning function as:

$$w(x, y) = f(I_{RGB}(i, j), I_{NIR}(i, j)) * \left(1 - \left(\frac{\min(DP(x, y), DP_{cutoff})}{DP_{cutoff}}\right)^{p}\right), \quad p \in (0, 1] \tag{5}$$

where DP_{cutoff} is a predefined cutoff disparity below which the see-through issue is negligible for the NIR image **502** and NIR and RGB fusion is allowed, and p is a control index what controls how fast the respective weight w(x,y) decreases with an increase of a disparity value DP(x,y). The predefined cutoff disparity DP_{cutoff} is also called a predefined maximum disparity that corresponds to a minimum depth above which the see-through issue is negligible for the NIR image **502** and the NIR and RGB fusion is allowed. In some embodiments, $f(I_{RGB}, I_{NIR})$ in equations (4) and (5) is a weight peak value determined based on one or more of a transmission level, a vegetation level and an infrared deviation level of an image patch. More details on the weight peak value $f(I_{RGB}, I_{NIR})$ are explained below with reference to FIGS. **7** and **8**.

As the depth value D(x,y) decreases from a predefined cutoff depth D_{cutoff} to 0, the disparity DP(x,y) increases from the predefined cutoff disparity DP_{cutoff} to the infinity, and the see-through effect is fully suppressed because the weight w(x,y) is equal to 0 (i.e., the NIR image layer **506** is not combined into the first combined image layer **512**). Conversely, as the depth value D(x,y) increases from the predefined cutoff depth D_{cutoff} to an infinite distance, the disparity DP(x,y) decreases from the predefined cutoff disparity DP_{cutoff} to 0, and the see-through effect is controlled with an increasing weight w(x,y). More details on a correlation of the weight w(x,y) and the disparity D(x,y) are explained below with reference to FIG. **10**.

After combining the first NIR and RGB image layers **506** and **508**, the computer system reconstructs a fused image **514** based on the first combined image layer **512**. In some embodiments, the first NIR layer **506** is identical to the NIR image **502**, while the RGB image **504** is decomposed to the first and second RGB image layers **508** and **510**. The first combined image layer **512** is combined with the second RGB image layer **510** to reconstruct the fused image **514**.

In some embodiments, a pyramid is applied to decompose RGB image **504**, when the RGB image **504** has a higher resolution than the NIR image **502**. The pyramid optionally includes a lowpass pyramid configured to smooth the RGB image **504** and subsampling the smoothed image **504** (e.g., by a factor of 2 along each coordinate direction) repeatedly in one or more cycles. Each cycle results in an image layer having a smaller resolution with increased smoothing. Stated another way, the pyramid corresponds to a plurality of image layers having a decreasing image resolution from a lower image layer to a higher image layer. Specifically, in a Gaussian pyramid, image layers are weighted down using a Gaussian average (Gaussian blur) and scaled down. Each pixel containing a local average corresponds to a neighborhood pixel on a lower image layer of the pyramid. In a Laplacian pyramid, a respective difference image is stored for each image layer, except that only the highest image layer is not a difference image, thereby allowing all of the image layers in the Laplacian pyramid to be reconstructed based on the highest image layer.

FIG. **6** is another example pyramid framework **600** fusing an NIR image **502** and an RGB image **504**, in accordance with some embodiments. The pyramid framework **600** is implemented at a computer system (e.g., a server **102**, a client device, or a combination thereof). The computer system obtains the NIR image **502** and RGB image **504** of a scene. The computer system generates a first NIR image layer **506** having a first resolution and a second NIR image layer **606** having a second resolution greater than the first resolution. The computer system also generates a first RGB image layer **508** and a second RGB image layer **608** from the RGB image **504**. The first RGB image layer **508** has the same resolution as the first NIR image layer **506**, and is therefore combined with the first NIR image layer **506** on a pixel-by-pixel basis to generate a first combined image layer **512**. The second RGB image layer **608** has the same resolution as the second NIR image layer **606**, and is therefore combined with the second NIR image layer **606** on a pixel-by-pixel basis to generate a second combined image layer **612**. A second depth map is also generated and has the second resolution of the second NIR and RGB image layers **606** and **608**. Each pixel of the second NIR image layer **606** and a corresponding pixel of the second RGB image layer **608** are generated based on a respective weight that is determined based on a depth value of a respective pixel of the second depth map and a predefined cutoff depth D_{cutoff}. The predefined cutoff depth D_{cutoff} is also applied to combine the first NIR and RGB image layers **506** and **508**. The computer system configured to implement the pyramid framework **600** is optionally the camera **104**D itself, the client device containing a camera that captures the NIR and RGB images, the server **102**, a distinct client device configured to review a fusion output of the framework **500**, or any combination of them.

In some embodiments, the NIR image **502** and the RGB image **504** have the same resolution, and are decomposed to two separate sets of image layers having the same number of layers (e.g., 2 layers). Each NIR image layer in the set of image layers corresponding to the NIR image **502** is combined with a respective RGB image layer in the set of image layers corresponding to the RGB image **504** to generate a respective combined image layer. The computer system reconstructs the fused image **514** based on all of the respective combined image layers (e.g., the first combined image layer **512** and the second combined image layer **612**).

In some embodiments, the NIR image **502** and the RGB image **504** have different resolutions, e.g., the NIR image **502** has a smaller resolution than the RGB image **504**. The NIR image **502** is used to generate the first and second NIR image layers **506** and **606**, while the RGB image **504** is used to generate the first and second RGB image layers **508** and **608** and a third RGB image layer **614**. The third RGB image layer **614** has a third resolution greater than the second resolution. The first RGB image layer **506** is combined with the first NIR image layer **508** on a pixel-by-pixel basis to generate the first combined image layer **512**. The second

RGB image layer **608** is combined with the second NIR image layer **606** on a pixel-by-pixel basis to generate the second combined image layer **612**. The fused image **514** is reconstructed from the first combined image layer **512**, the second combined image layer **612**, and the third RGB image layer **614**.

In some embodiments, a pyramid is applied to decompose each of the NIR and RGB images **502** and **504**, independently of whether the NIR and RGB images **502** and **504** have the same resolution. Each pyramid optionally includes a lowpass pyramid configured to smooth the respective image **502** or **504** and subsampling the smoothed image (e.g., by a factor of 2 along each coordinate direction) repeatedly in one or more cycles. Each cycle results in an image layer having a smaller resolution with increased smoothing. Stated another way, for each of the NIR and RGB images **502** and **504**, a respective pyramid corresponds to a plurality of image layers having a decreasing image resolution from a lower image layer to a higher image layer, and two image layers of different pyramids having the same resolutions are combined based on a respective weight (e.g., a respective depth-based weight). In some embodiments, the NIR and RGB images **502** and **504** are decomposed according to Gaussian pyramids. Alternatively, in some embodiments, the NIR and RGB images **602** and **604** are decomposed according to Laplacian pyramids.

FIG. **7** illustrates an example process **700** of generating a weight map **702** for fusing an NIR image **502** and an RGB image **504**, in accordance with some embodiments. The weight map **702** includes a plurality of weights w(x,y), and each weight w(x,y) is applied to combine pixels located at a pixel position (x, y) of an NIR image layer **704** and an RGB image layer **706**. As described above, the NIR image layer **704** is the NIR image **502** or one of a plurality of NIR image layers (e.g., the NIR image layers **506** and **606**) decomposed from the NIR image **502**, and the RGB image layer **706** is one of a plurality of RGB image layers (e.g., the RGB image layers **508**, **608** and **614**) decomposed from the RGB image **504**. The NIR image layer **704**, RGB image layer **706**, and weight map **702** have the same resolution, such that the NIR image layer **704** and RGB image layer **706** can be combined to a combined image layer **708** using the weight map **702**. Specifically, each pixel of the NIR image layer **704** and a corresponding pixel of the RGB image layer **706** are combined based on a respective weight w(x,y) of the weight map **702**.

The weight map **702** is determined from at least a depth map **710** that contains information of a distance measured from a surface of an object that is captured in the NIR and RGB images **502** and **504** to lenses of a camera applied to capture the images **502** and **504**. In some embodiments, the depth map **710** is determined based on the RGB image layer **706**. In some embodiments, a depth value of each pixel of the depth map **710** represents a true distance measured from the surface of the corresponding object located at the pixel to the camera. Alternatively, in some embodiments, the depth map **710** corresponds to a disparity map of a scene, and the disparity map can be converted to an absolute image depth given a baseline and camera parameters of the camera used to capture the RGB image **504**. Referring to equation (4), in some embodiments, the depth map **710** is established based on a predefined cutoff depth D_{cutoff}. When a depth value is less than the predefined cutoff depth D_{cutoff}, the respective weight w(x,y) is optionally equal to zero or less than when the depth value is greater than the predefined cutoff depth D_{cutoff}. For example, in an example related to equation (4), the respective weight w(x,y) is not equal to zero when the depth value is less than the predefined cutoff depth D_{cutoff}, and in another example related to equation (5), the respective weight w(x,y) is equal to zero as the parity DP(x,y) is greater than a predefined cutoff parity DP_{cutoff} (i.e., as the depth value D(x,y) is less than the cutoff depth D_{cutoff}), and increases as the parity DP(x,y) drops from the cutoff parity DP_{cutoff} to 0 (i.e., as the depth value D(x,y) increases from the cutoff depth D_{cutoff} to an infinite distance). This prevents details that are contained in the NIR image layer **704** and related to an object located near the camera from being fused into the combined image layer **708**.

Additionally, in some embodiments, the weight map **702** is determined from a combination of the depth map **710** and at least one of a transmission map **712** and a vegetation map **714**. It is noted that a depth-based control portion in equations (4) and (5) is determined based on the depth map **710** and that a weight peak value $f(I_{RGB}, I_{NIR})$ in equations (4) and (5) is determined based on the transmission map **712** and/or vegetation map **714**. Each of the transmission map **712** and vegetation map **714** has the same resolution as the NIR and RGB image layers **704** and **706**. The transmission map **712** describes a portion of light that is not scattered and reaches a camera that captures the RGB image **504**, and is optionally generated from the RGB image layer **706**. The vegetation map **714** provides optical measures of vegetation canopy "greenness" and gives a direct measure of photosynthetic potential resulting from the composite property of total leaf chlorophyll, leaf area, canopy cover, and structure. The vegetation map **714** is optionally generated from both the NIR image layer **704** and RGB image layer **706**. Each of the transmission map **712** and vegetation map **714** can provide additional information concerning whether details in each pixel need to be reduced from the combined image layer **708**. As such, each weight w(x,y) of the weight map **702** is generated based on a combination of corresponding pixel values in the depth map **710** and one or both of the transmission map **712** and vegetation map **714**.

FIG. **8** is a flowchart of an overall process **800** of fusing an NIR image **502** and an RGB image **504** using a depth-based weight map **702**, in accordance with some embodiments. One or more NIR image layers **704** are generated from the NIR image **502**. A plurality of RGB image layers **706** are generated from the RGB image **504**. In an example shown in FIG. **5**, the NIR image **502** is converted to a single NIR image layer **506** having a first resolution, and the plurality of RGB image layers **706** include a first RGB image layer **508** having the first resolution and a second RGB image layer having a second resolution larger than the first resolution. In another example shown in FIG. **6**, the NIR image **502** is converted to the NIR image layers **704** that include at least a first NIR image layer **506** having a first resolution and a second NIR image layer **606** having a second resolution larger than the first resolution. The RGB image layers **706** include at least a first RGB image layer **508** having the first resolution and a second RGB image layer **608** having the second resolution. Further, in some embodiments, the RGB image layers **706** include a third image layer **614** having a third resolution larger than the first and second resolutions. In some embodiments, each of the RGB image layers **706** is part of a Laplacian pyramid **802** including a plurality of image layers decomposed from the RGB image **504**, and may be adjusted based on an atmosphere light level **804**.

In some embodiments, each RGB image layer **706** is converted (**606**) from an RGB color space to a CIELAB color space (i.e., L*a*b*) in which color information is expressed as a lightness channel (L*) **808** and two unique color channels, in which color information is expressed as lightness channel (L*) **808** and two unique color channels (a* and b*). The channel **808** of the first RGB layer **508** having the lowest resolution corresponds to a channel L base portion **812**, while the channel **808** of each RGB image layer having a higher resolution (e.g., the layer **510**, **608**, or **615**) corresponds to a respective channel L detail portion **814**. Similarly, the first NIR image layer **506** having the lowest resolution corresponds to an NIR base portion **816**, while each NIR image layer having a higher resolution (e.g., the layer **606**) corresponds to a respective NIR detail portion **818**. In some embodiments, the NIR image **502** and the RGB image **504** are combined by combining (**620**) the channel L and NIR base portions **812** and **816** separately and using a first weight setting **822**, combining (**628**) the channel L and NIR detail portions **814** and **818** using a second weight setting **826**, and fusing (**628**) a combined detail portion and a combined base portion. Referring to FIG. **6**, the combined detail and base portions correspond to the first and second combined image layers **512** and **612**, respectively. The fused portions are associated with the lightness channel **808**, and can be recombined with the color information of the two unique color channels (a* and b*).

In some embodiments, the first weight setting **822** used to combine the channel L and NIR base portions **812** and **816** is determined based on a weight map **702**. The weight map **702** is based on at least a depth map **710** that is optionally derived from the RGB image **504**. The second weight setting **826** used to combine the channel L and NIR detail portions **814** and **818** is determined based on the depth map **710**. In some situations, the weight map **702** is based on a combination of the depth map **710** and the transmission map **712**. Alternatively, in some situations, the weight map **702** is based on a combination of the depth map **710** and the vegetation map **714**. Additionally and alternatively, in some situations, the weight map **702** is based on a combination of the depth map **710**, the transmission map **712**, and the vegetation map **714**. Specifically, for the weight map **702** described in equation (4) or (5), a depth-based control portion is determined based on the depth map **710**, and a weight peak value $f(I_{RGB}, I_{NIR})$ is determined based on the transmission map **712** and/or vegetation map **714**. More details on generating the depth map **710** are explained below with reference to FIG. **9**.

In some implementations, the first weight setting **822** (i.e., the weight map **702**) used to combine the channel L and NIR base portions **812** and **816** is determined based on the depth map **710** and a deviation map **830**. The deviation map **830** is determined based on an IR deviation map **832** or the vegetation map **714**. The vegetation map **714** is optionally determined based on the corresponding NIR image layer **704**, the depth map **710**, and a red channel **834** split from the RGB image layer **706**. The IR deviation map **832** may be determined based on the NIR image layer **704**, and the color information of the lightness channel **808**. As such, the first weight setting **822** (i.e., the weight map **702**) is determined based on the IR deviation map **832**, vegetation map **714**, and depth map **710**. Stated another way, for the weight map **702** described in equation (4) or (5), the depth map **710** determines a depth-based control portion, and the depth map **710** and at least one of the IR deviation map **832** and vegetation map **714** jointly determine a weight peak value $f(I_{RGB}, I_{NIR})$ in equations (4) and (5).

FIG. **9** is a flowchart of a process **900** of generating a depth map **710** based on an RGB image **504**, in accordance with some embodiments. The RGB image **504** is scaled (**902**) down to a depth resolution, and provided to a deep learning model **904** that is optionally trained using a large depth dataset MegaDepth. MegaDepth uses multi-view Internet photo collections, a virtually unlimited data source, to generate training data via modern structure-from-motion and multi-view stereo (MVS) methods. The MegaDepth-trained deep learning model **904** outputs a depth image **905** that has the depth resolution and is further scaled up to a preliminary depth map **908** having a target resolution. In some embodiments, a guided filter **910** is applied to process the preliminary depth map **908** to filter out noise or texture while retaining sharp edges of the preliminary depth map **908**, thereby generating a filtered depth map **912**. One of the preliminary and filtered depth maps **908** and **912** is applied as the depth map **710**. The depth map **710** can be further used to generate a weight map **702** based on which an NIR image layer **704** and an RGB image layer **706** are combined.

Conversely, in some embodiments not shown in FIG. **9**, the depth map **710** having the first resolution is generated from the RGB image **504** and the NIR image **502** using a stereo depth estimation model rather than the MegaDepth-trained deep learning model **904**.

FIG. **10** is a diagram illustrating a depth-based control portion **1000** of an example weight assigning function, in accordance with some embodiments. The depth map **710** corresponds to a parity map. The depth-based control portion **1000** of the weight assigning function in equation (5) is determined based on the parity map as follows:

$$1-\left(\frac{\min(DP(x,y), DP_{cutoff})}{DP_{cutoff}}\right)^{p}, p\in(0,1] \tag{6}$$

wherein DP(x,y) is a disparity value of a respective pixel located at a position (x,y) in the disparity map corresponding to the depth map **710**. In some embodiments, the control index p is in a range of [0.5, 0.8]. Each disparity value DP(x,y) in the disparity map is correlated with a reciprocal of the image depth D(x,y) given a baseline and camera parameters (e.g., a focal length) of the camera used to capture the RGB image **504**. Each disparity value is measured in pixels, e.g., equal to 20 or 30 pixels. In an example, the control index is equal to 0.5. the predefined cutoff depth DP_{cutoff} is equal to 20 pixels.

Specifically, as the depth value D(x,y) decreases from the cutoff depth D_{cutoff} to 0, the disparity DP(x,y) increases from the predefined cutoff disparity DP_{cutoff} to the infinity, and the see-through effect is fully suppressed because the depth-based control portion **1000** and weight w(x,y) are equal to 0 (i.e., the NIR image layer **506** is not combined into the combined image layer **514**). Conversely, as the depth value D(x,y) increases from the predefined cutoff depth D_{cutoff} to an infinite distance, the disparity DP(x,y) decreases from the predefined cutoff disparity DP_{cutoff} to 0, and the see-through effect is controlled with an increasing depth-based control portion **1000** and weight w(x,y). As shown in FIG. **10**, the depth-based control portion **1000** of the weight assigning function in equation (5) is equal to 0 when the parity value DP is greater than 20 pixels, and is represented as

$$1-\sqrt{\frac{DP(x,y)}{20}}$$

when the parity value DP is not greater than 20 pixels.

FIG. **11** is a flow diagram of an image fusion method **1100** implemented at a computer system, in accordance with some embodiments. The method **1100** is, optionally, governed by instructions that are stored in a non-transitory computer readable storage medium and that are executed by one or more processors of the computer system (e.g., a server **102**, a client device **104**, or a combination thereof). Each of the operations shown in FIG. **11** may correspond to instructions stored in the computer memory or computer readable storage medium (e.g., memory **206** in FIG. **2**) of the computer system **200**. The computer readable storage medium may include a magnetic or optical disk storage device, solid state storage devices such as Flash memory, or other non-volatile memory device or devices. The computer readable instructions stored on the computer readable storage medium may include one or more of: source code, assembly language code, object code, or other instruction format that is interpreted by one or more processors. Some operations in method **1100** may be combined and/or the order of some operations may be changed. More specifically, the method **1100** is governed by instructions stored in a depth-based image processing module **250**, a data processing module **228**, or both in FIG. **2**.

The computer system obtains (**1102**) an NIR image **502** and an RGB image **504** of a scene. A first NIR image layer **506** having a first resolution is generated (**1104**) from the NIR image **502**. A first RGB image layer **508** and a second RGB image layer **510** are generated (**1106**) from the RGB image **504**. The first RGB image layer **508** has the first resolution. A depth map **710** is generated (**1108**), e.g., from the RGB image **504**, and has the first resolution. The computer system generates a first combined image layer by combining (**1110**) each pixel of the first NIR image layer **506** and a corresponding pixel of the first RGB image layer **508** based on a respective weight w(x,y) that is determined based on a depth value D(x,y) of a respective pixel of the depth map **710** and a predefined cutoff depth D_{cutoff}. A fused image **514** is reconstructed (**1112**) based on the first combined image layer **512**. In some embodiments, the predefined cutoff depth D_{cutoff} is between 5 and 10 meters.

In some embodiments, for each pixel of the first NIR image layer **506**, in accordance with a determination that the depth value of the respective pixel of the depth map **710** is greater than or equal to the predefined cutoff depth D_{cutoff}, the computer system determines the respective weight w(x, y) for the respective pixel of the first NIR image layer **506** based on a two dimensional position (x, y) of the respective pixel on the first NIR image layer **506**. The respective weight w(x,y) is based on a respective first weight (i.e., a weight peak value $f(I_{RGB}, I_{NIR})$ in equations (4) and (5)) independently of a magnitude of the depth value D(x,y). Further, in some embodiments, for each pixel of the first NIR image layer **508**, in accordance with a determination that the depth value D(x,y) of the respective pixel of the depth map **710** is less than the predefined cutoff depth D_{cutoff}, a value of the respective weight w(x,y) is scaled for the respective pixel of the first NIR image layer **506** from the respective first weight value based on the depth value D(x,y) of the respective pixel of the depth map **710**. Referring to equation (4) or (5), in some embodiments, the value of the respective weight w(x,y) is scaled from the respective first weight value (i.e., a weight peak value $f(I_{RGB}, I_{NIR})$) nonlinearly based on the depth value D(x,y) of the respective pixel of the depth map **710**.

In some embodiments, each pixel of the first NIR image layer **506** and a corresponding pixel of the first RGB image layer **508** is combined according to equation (1). Further, in some embodiments, for each pixel, the respective weight w(x,y) is represented as equation (5) including a control index p. In an example, the control index p is in a range of [0.5, 0.8].

In some embodiments, prior to combining each pixel of the first NIR image layer **506** and the corresponding pixel of the first RGB image layer **508**, the computer system determines the respective weight w(x,y) at least partially based on a haze level in the RGB image **504** and/or a reflection rate in the NIR image **502**. For example, referring to FIG. **6**, atmosphere light is monitored (**802**) to determine how heavy is the haze in the RGB image **504**, and infrared deviation is monitored (**832**) and a vegetation map is created (**514**) for generating the respective weight w(x,y), particularly when the reflection rate of the NIR image **502** is higher than that of the RGB image **504**.

In some embodiments, the first NIR image layer **506** is identical to the NIR image **502**, and the RGB image **504** is converted to the first and second RGB image layers **508** and **510** via Laplacian decomposition. The fused image **514** is reconstructed from the first combined image layer **512** and the second RGB image layer **510**.

Referring to FIG. **6**, in some embodiments, the second RGB image layer **608** has a second resolution greater than the first resolution, and the depth map **710** includes a first depth map. The computer system generates a second NIR image layer **606** having the second resolution from the NIR image **502**, and a second depth map having the second resolution. A second combined image layer **612** is generated by combining each pixel of the second NIR image layer **406** and a corresponding pixel of the second RGB image layer **408** based on a respective weight that is determined based on a depth value of a respective pixel of the second depth map and the predefined cutoff depth D_{cutoff}. The fused image **514** is reconstructed from the first combined image layer **512** and the second combined image layer **612**.

Also, referring to FIG. **6**, in some embodiments, the depth map **710** includes a first depth map. The computer system generates a second NIR image layer **606** having a second resolution from the NIR image **502**, and a second depth map having the second resolution. The second resolution is greater than the first resolution. The computer system generates a third RGB image layer **614** having a third resolution from the RGB image. A second combined image layer **612** is generated by combining each pixel of the second NIR image layer **606** and a corresponding pixel of the second RGB image layer **608** based on a respective weight that is determined based on a depth value of a respective pixel of the second depth map and the predefined cutoff depth D_{cutoff}. The fused image is reconstructed from the first combined image layer **512**, the second combined image layer **612**, and the third RGB image layer **614**. Further, in some embodiments, the second NIR image layer **606** is converted from the NIR image **502** via Laplacian decomposition, and the first, second, and third RGB image layers **508**, **608**, and **614** are converted from the RGB image via Laplacian decomposition and form a Laplacian pyramid.

Referring to FIG. **9**, in some embodiments, the depth map **710** having the first resolution is generated by generating a depth image **905** having a depth resolution from the RGB image **504** and scaling the depth image **905** having the depth resolution to the depth map **710** having the first resolution. Further, in some embodiments, a deep learning model **904** is trained using training data (e.g., MegaDepth). The deep learning model **904** is configured to generate depth information corresponding to pixels in a single RGB image **302**. The RGB image **504** is scaled (**902**) based on an input requirement of the deep learning model **904**. The depth image **905** is generated using the scaled RGB image using the deep learning model **904**.

In some embodiments, the depth map **710** having the first resolution is generated from the RGB image **504** and the NIR image **502** using a stereo depth estimation model.

In some embodiments, the method **1100** is implemented by a client device **104** having a camera. The RGB image **504** and NIR image **502** are captured using a primary sensor and a secondary sensor of the camera, respectively. The RGB image **504** has a resolution equal to or greater than that of the NIR image **502**.

In some embodiments, the method **1100** is implemented at a server **102**. The NIR and RGB images **502** and **504** are received from a client device **104**. The client device **104** is configured to capture the RGB and NIR image using a primary sensor and a secondary sensor of the electronic device **104**, respectively. The RGB image **504** has a resolution greater than or equal to that of the NIR image **502**.

It should be understood that the particular order in which the operations in FIG. **11** have been described are merely exemplary and are not intended to indicate that the described order is the only order in which the operations could be performed. One of ordinary skill in the art would recognize various ways to fuse images as described herein. Additionally, it should be noted that details described above with respect to FIGS. **5-10** are also applicable in an analogous manner to the method **1100** described above with respect to FIG. **11**. For brevity, these details are not repeated here.

In one or more examples, the functions described may be implemented in hardware, software, firmware, or any combination thereof. If implemented in software, the functions may be stored on or transmitted over, as one or more instructions or code, a computer-readable medium and executed by a hardware-based processing unit. Computer-readable media may include computer-readable storage media, which corresponds to a tangible medium such as data storage media, or communication media including any medium that facilitates transfer of a computer program from one place to another, e.g., according to a communication protocol. In this manner, computer-readable media generally may correspond to (1) tangible computer-readable storage media which is non-transitory or (2) a communication medium such as a signal or carrier wave. Data storage media may be any available media that can be accessed by one or more computers or one or more processors to retrieve instructions, code and/or data structures for implementation of the embodiments described in the present disclosure. A computer program product may include a computer-readable medium.

The terminology used in the description of the embodiments herein is for the purpose of describing particular embodiments only and is not intended to limit the scope of claims. As used in the description of the embodiments and the appended claims, the singular forms "a," "an," and "the" are intended to include the plural forms as well, unless the context clearly indicates otherwise. It will also be understood that the term "and/or" as used herein refers to and encompasses any and all possible combinations of one or more of the associated listed items. It will be further understood that the terms "comprises" and/or "comprising," when used in this specification, specify the presence of stated features, elements, and/or components, but do not preclude the presence or addition of one or more other features, elements, components, and/or groups thereof.

It will also be understood that, although the terms first, second, etc. may be used herein to describe various elements, these elements should not be limited by these terms. These terms are only used to distinguish one element from another. For example, a first electrode could be termed a second electrode, and, similarly, a second electrode could be termed a first electrode, without departing from the scope of the embodiments. The first electrode and the second electrode are both electrodes, but they are not the same electrode.

The description of the present disclosure has been presented for purposes of illustration and description, and is not intended to be exhaustive or limited to the invention in the form disclosed. Many modifications, variations, and alternative embodiments will be apparent to those of ordinary skill in the art having the benefit of the teachings presented in the foregoing descriptions and the associated drawings. The embodiment was chosen and described in order to best explain the principles of the invention, the practical disclosure, and to enable others skilled in the art to understand the invention for various embodiments and to best utilize the underlying principles and various embodiments with various modifications as are suited to the particular use contemplated. Therefore, it is to be understood that the scope of claims is not to be limited to the specific examples of the embodiments disclosed and that modifications and other embodiments are intended to be included within the scope of the appended claims.

What is claimed is:

1. A method for image fusion, comprising:

obtaining a near infrared (NIR) image and an RGB image of a scene;

generating a first NIR image layer having a first resolution from the NIR image;

generating a first RGB image layer and a second RGB image layer from the RGB image, the first RGB image layer having the first resolution;

generating a depth map having the first resolution;

generating a first combined image layer, including combining each pixel of the first NIR image layer and a corresponding pixel of the first RGB image layer based on a respective weight that is determined based on a depth value of a respective pixel of the depth map and a predefined cutoff depth; and

reconstructing a fused image based on the first combined image layer.

2. The method of claim **1**, further comprising for each pixel of the first NIR image layer:

in accordance with a determination that the depth value of the respective pixel of the depth map is greater than or equal to the predefined cutoff depth, determining the respective weight for the respective pixel of the first NIR image layer based on a two dimensional position (x, y) of the respective pixel on the first NIR image layer, wherein the respective weight is based on a respective first weight independently of a magnitude of the depth value.

3. The method of claim **2**, further comprising for each pixel of the first NIR image layer:

in accordance with a determination that the depth value of the respective pixel of the depth map is less than the predefined cutoff depth, scaling a value of the respective weight for the respective pixel of the first NIR image layer from the respective first weight value based on the depth value of the respective pixel of the depth map.

4. The method of claim **3**, wherein the value of the respective weight is scaled from the respective first weight value nonlinearly based on the depth value of the respective pixel of the depth map.

5. The method of claim **1**, wherein each pixel of the first NIR image layer and a corresponding pixel of the first RGB image layer is combined as follows:

$$I_{COMB}(x,y)=\mathrm{w}(x,y)\times I_{NIR}(x,y)+(1-w(x,y))\times I_{RGB}(x,y)$$

where IRGB(x,y) and INIR(x,y) are values of the respective pixel located at a position (x,y) in the first RGB image layer and the first NIR image layer, respectively, and w(x,y) is the respective weight.

6. The method of claim **5**, wherein for each pixel, the respective weight is represented as:

$$w(x, y) = f(I_{RGB}(x, y), I_{NIR}(x, y)) * \min\left(1, \log_p\left(\max\left(1, \frac{D(x, y)}{D_{cutoff}}\right)\right)\right),$$
$$p \in (1, \infty]$$

where D(x,y) is the depth value of the respective pixel located at the position (x,y) in the depth map, Dcufoff is the predefined cutoff depth, $f(I_{RGB}(x, y), I_{NIR}(x, y))$ is a weight peak value, and p is a control index.

7. The method of claim **5**, wherein for each pixel, the respective weight is represented as:

$$w(x, y) = f(I_{RGB}(x, y), I_{NIR}(x, y)) \times \left(1 - \left(\frac{\min(D(x, y), D_{cutoff})}{D_{cutoff}}\right)^p\right),$$
$$p \in (0, 1]$$

where DP(x,y) is a disparity value of the respective pixel located at the position (x,y) in a disparity map, Dcufoff is a predefined cutoff disparity, $f(I_{RGB}(x, y), I_{NIR}(x, y))$ is a weight peak value, and p is a control index, and wherein the disparity value is associated with the depth value, and the predefined cutoff disparity is associated with the predefined cutoff depth.

8. The method of claim **1** further comprising, prior to combining each pixel of the first NIR image layer and the corresponding pixel of the first RGB image layer:

determining the respective weight at least partially based on a haze level in the RGB image and/or a reflection rate in the NIR image.

9. The method of claim **1**, wherein the predefined cutoff depth is between 5 and 10 meters.

10. The method of claim **1**, wherein the first NIR image layer is identical to the NIR image, and the RGB image is converted to the first and second RGB image layers via Laplacian decomposition, and wherein the fused image is reconstructed from the first combined image layer and the second RGB image layer.

11. The method of claim **1**, wherein the second RGB image layer has a second resolution greater than the first resolution, and the depth map includes a first depth map, the method further comprising:

generating a second NIR image layer having the second resolution from the NIR image;

generating a second depth map having the second resolution;

generating a second combined image layer, including combining each pixel of the second NIR image layer and a corresponding pixel of the second RGB image layer based on a respective weight that is determined based on a depth value of a respective pixel of the second depth map and the predefined cutoff depth; and

wherein the fused image is reconstructed from the first combined image layer and the second combined image layer.

12. The method of claim **1**, wherein the depth map includes a first depth map, the method further comprising:

generating a second NIR image layer having a second resolution from the NIR image, the second resolution being greater than the first resolution;

generating a second depth map having the second resolution;

generating a third RGB image layer having a third resolution from the RGB image; and

generating a second combined image layer, including combining each pixel of the second NIR image layer and a corresponding pixel of the second RGB image layer based on a respective weight that is determined based on a depth value of a respective pixel of the second depth map and the predefined cutoff depth;

wherein the fused image is reconstructed from the first combined image layer, the second combined image layer, and the third RGB image layer.

13. The method of claim **12**, wherein the second NIR image layer is converted from the NIR image via Laplacian decomposition, and the first, second, and third RGB image layers are converted from the RGB image via Laplacian decomposition and form a Laplacian pyramid.

14. The method of claim **1**, wherein generating the depth map having the first resolution further includes:

generating a depth image having a depth resolution from the RGB image; and

scaling the depth image having the depth resolution to the depth map having the first resolution.

15. The method of claim **14**, further comprises:

training a deep learning model using training data, the deep learning model configured to generate depth information corresponding to pixels in a single RGB image;

scaling the RGB image based on an input requirement of the deep learning model;

generating the depth image using the scaled RGB image using the deep learning model.

16. The method of claim **1**, wherein the depth map having the first resolution is generated from the RGB image and the NIR image using a stereo depth estimation model.

17. The method of claim **1**, wherein the method is implemented by an electronic device having a camera, and obtaining the NIR image and RGB image further comprises:

capturing the RGB image and NIR image using a primary sensor and a secondary sensor of the camera, respectively, the RGB image having a resolution greater than that of the NIR image.

18. The method of claim **1**, wherein the method is implemented at a server, and obtaining the NIR image and RGB image further comprises:

receiving from a client device the RGB and NIR images, wherein the client device is configured to capture the RGB and NIR image using a primary sensor and a secondary sensor of an electronic device, respectively, and the RGB image has a resolution greater than that of the NIR image.

19. A computer system, comprising:

one or more processors; and

memory having instructions stored thereon, which when executed by the one or more processors cause the processors to:

obtain a near infrared (NIR) image and an RGB image of a scene;

generate a first NIR image layer having a first resolution from the NIR image, and generate a first RGB image layer having the first resolution from the RGB image;

generate a depth map having the first resolution;

generate a first combined image layer, including combining each pixel of the first NIR image layer and a corresponding pixel of the first RGB image layer based on a respective weight that is determined based on a depth value of a respective pixel of the depth map and a predefined cutoff depth; and

reconstruct a fused image based on the first combined image layer.

20. A non-transitory computer-readable medium, having instructions stored thereon, which when executed by one or more processors cause the processors to:

obtain a near infrared (NIR) image and an RGB image of a scene, the NIR image having a first resolution;

generate a first RGB image layer and a second RGB image layer from the RGB image, the first RGB image layer having the first resolution, the second RGB image layer having a second resolution which is greater than the first resolution;

generate a depth map having the first resolution;

generate a first combined image layer, including combining each pixel of the first NIR image and a corresponding pixel of the first RGB image layer based on a respective weight that is determined based on a depth value of a respective pixel of the depth map and a predefined cutoff depth; and

reconstruct a fused image based on the first combined image layer and the second RGB image layer.

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