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Nadir et al.

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(54) **SYSTEM AND METHOD FOR FACIAL UN-DISTORTION IN DIGITAL IMAGES USING MULTIPLE IMAGING SENSORS**

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G06T 7/40	(2017.01)
G06T 7/50	(2017.01)

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(58) **Field of Classification Search**

None

See application file for complete search history.

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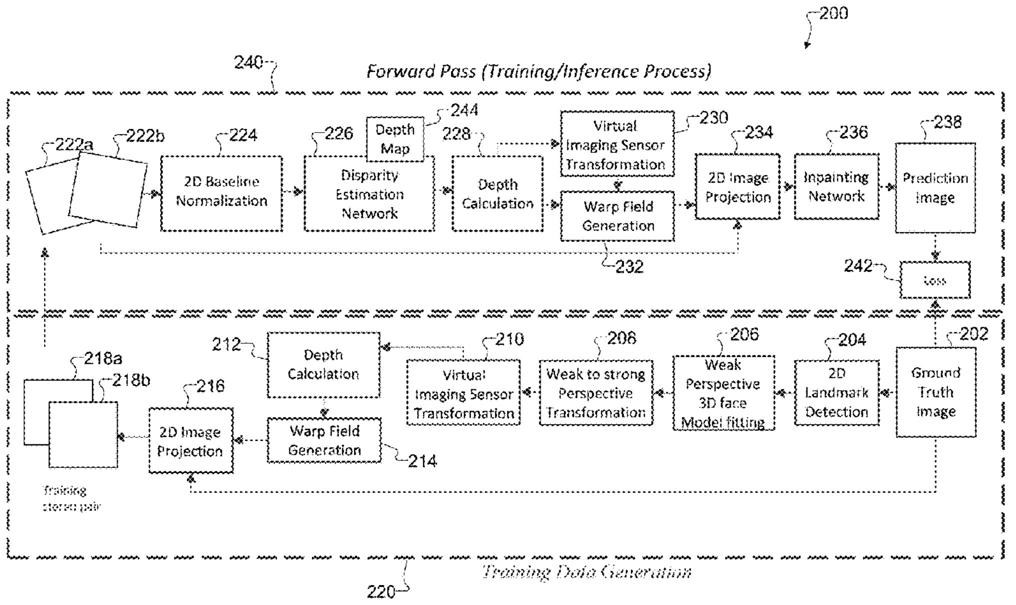
Primary Examiner — Leon Viet Q Nguyen

(57) **ABSTRACT**

A method includes aligning landmark points between multiple distorted images to generate multiple aligned images, where the multiple distorted images exhibit perspective distortion in at least one face appearing in the multiple distorted images. The method also includes predicting a depth map using a disparity estimation neural network that receives the multiple aligned images as input. The method further includes generating a warp field using a selected one of the multiple aligned images. The method also includes performing a two-dimensional (2D) image projection on the selected aligned image using the depth map and the warp field to generate an undistorted image. In addition, the method includes filling in one or more missing pixels in the undistorted image using an inpainting neural network to generate a final undistorted image.

24 Claims, 12 Drawing Sheets



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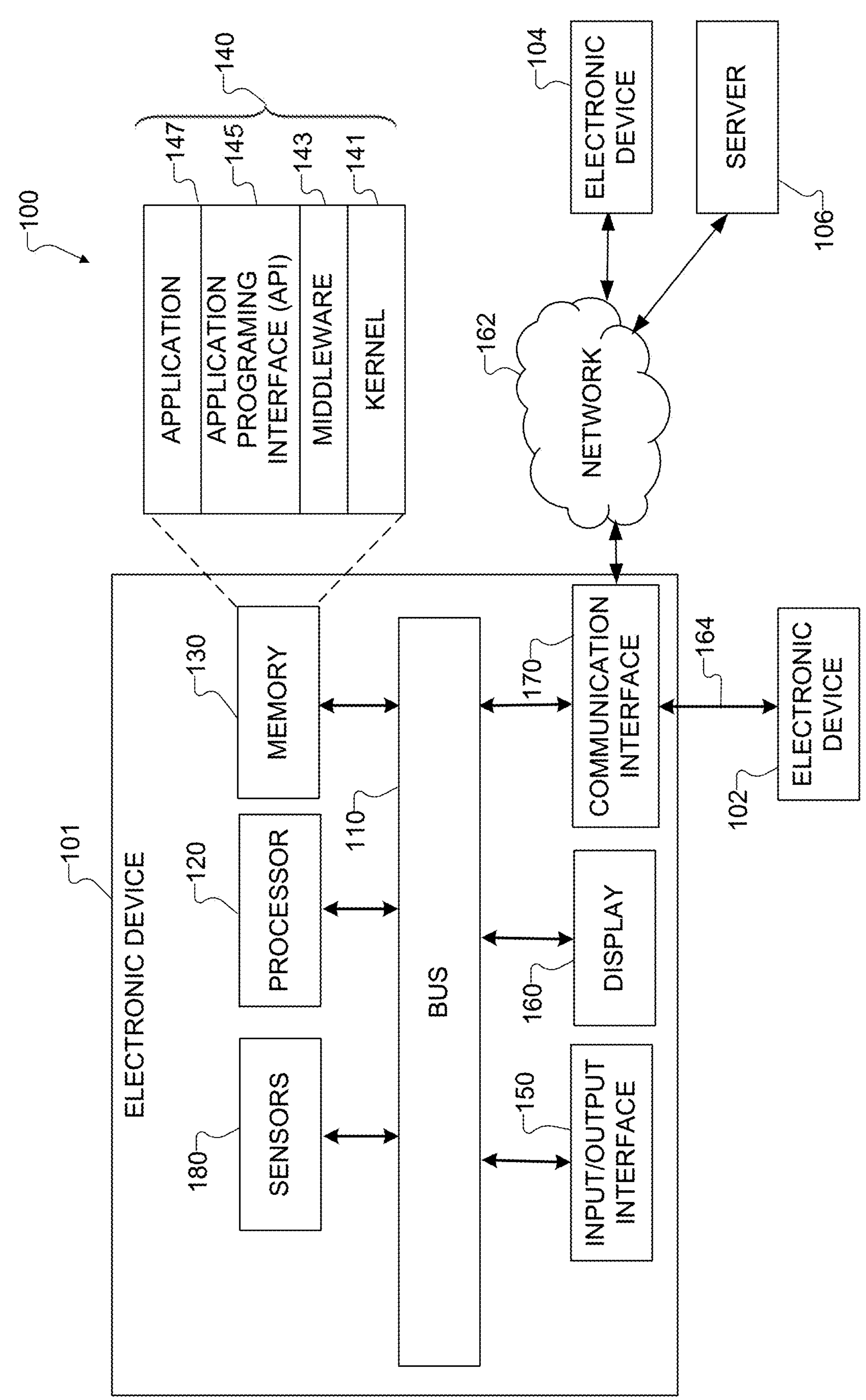

100
140
147
145
143
141
APPLICATION
APPLICATION PROGRAMING INTERFACE (API)
MIDDLEWARE
KERNEL
104
ELECTRONIC DEVICE
SERVER
106
162
NETWORK
101
ELECTRONIC DEVICE
130
MEMORY
120
PROCESSOR
180
SENSORS
110
BUS
170
COMMUNICATION INTERFACE
160
DISPLAY
150
INPUT/OUTPUT INTERFACE
164
102
ELECTRONIC DEVICE

FIG. 1

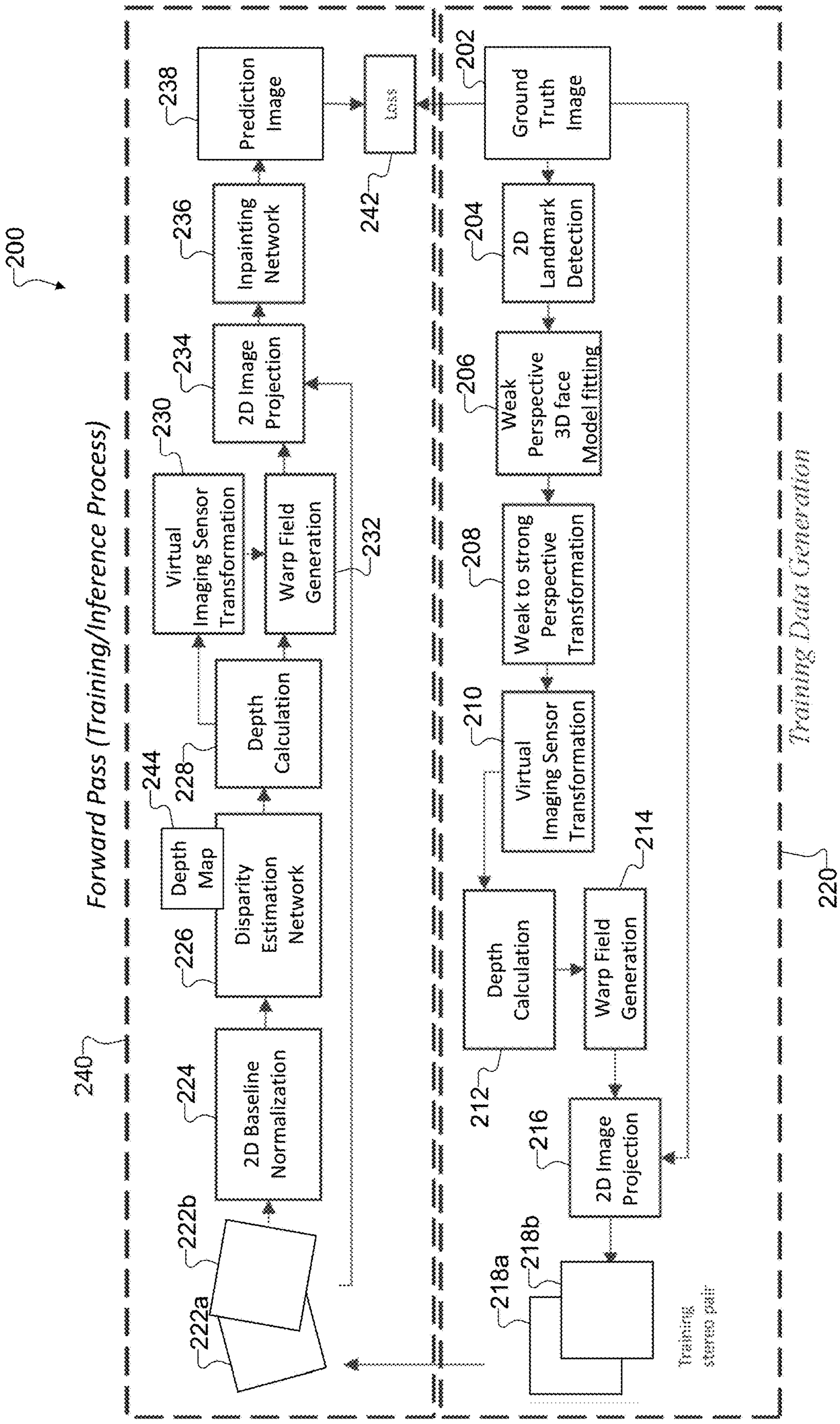

200
Forward Pass (Training/Inference Process)
240
222a
222b
224
2D Baseline Normalization
226
Disparity Estimation Network
244
Depth Map
228
Depth Calculation
230
Virtual Imaging Sensor Transformation
232
Warp Field Generation
234
2D Image Projection
236
Inpainting Network
238
Prediction Image
242
Loss
202
Ground Truth Image
204
2D Landmark Detection
206
Weak Perspective 3D face Model fitting
208
Weak to strong Perspective Transformation
210
Virtual Imaging Sensor Transformation
212
Depth Calculation
214
Warp Field Generation
216
2D Image Projection
218a
218b
Training stereo pair
Training Data Generation
220

FIG. 2A

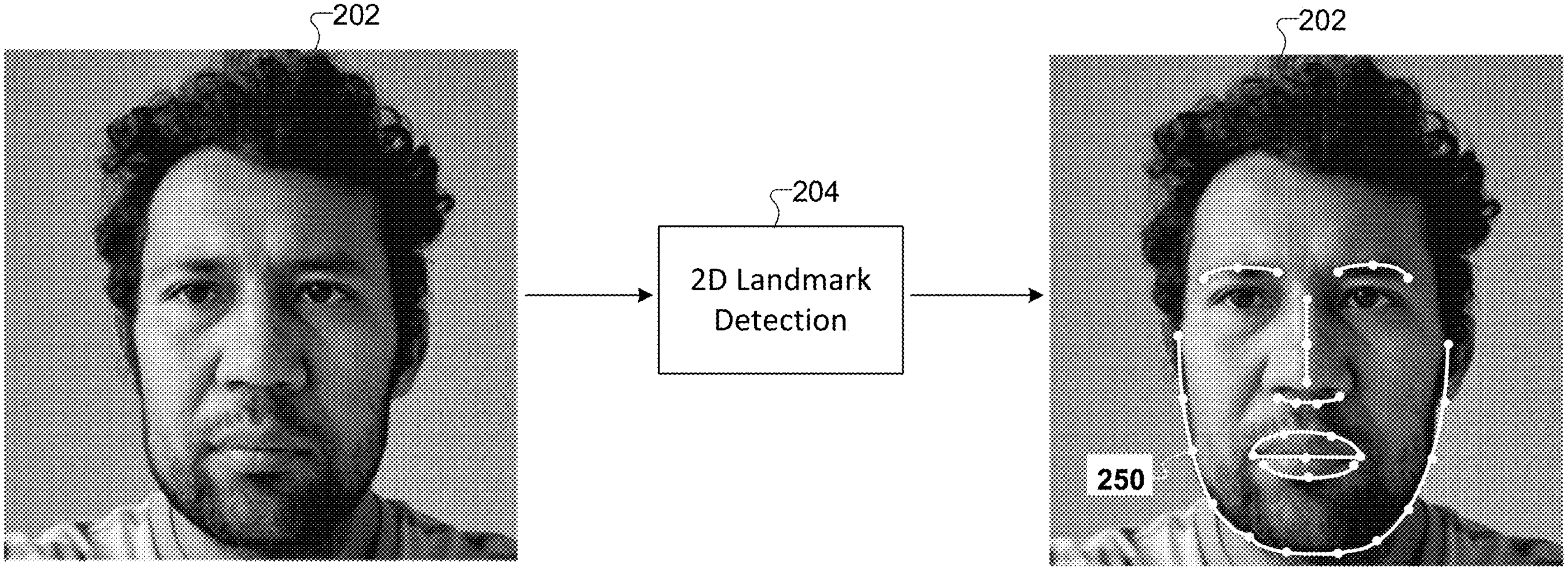


FIG. 2B

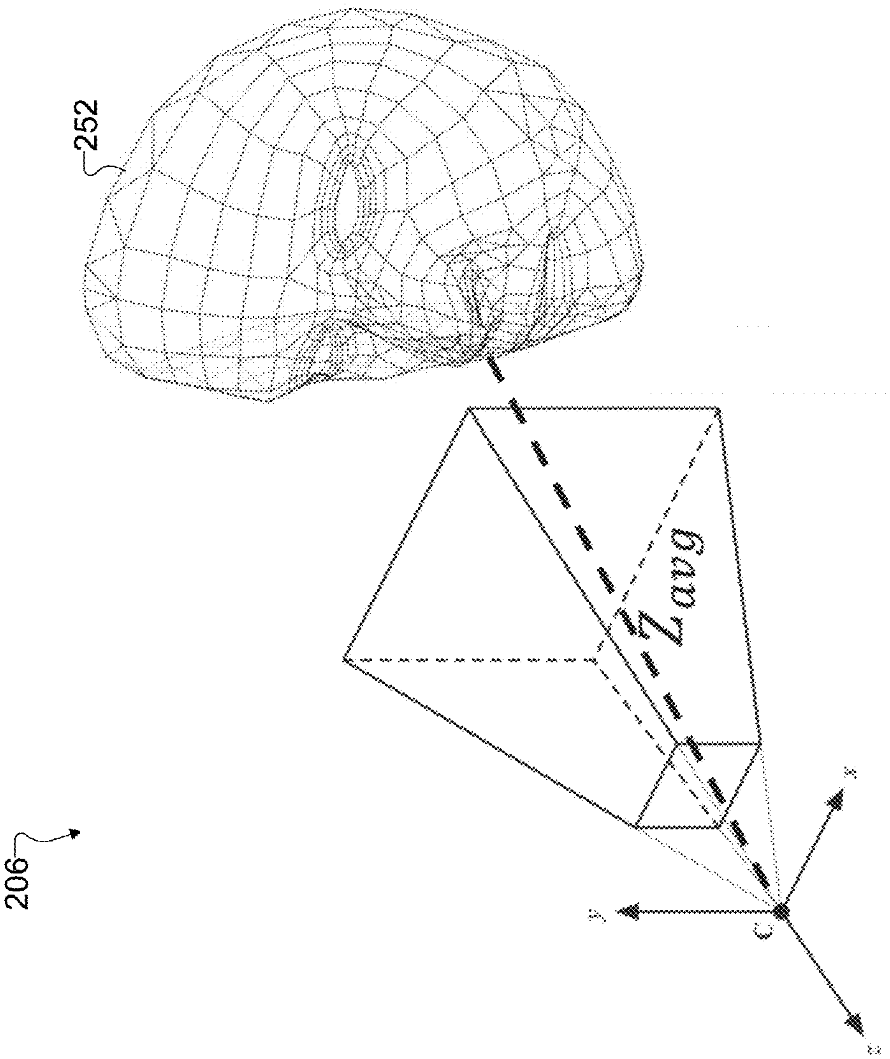


FIG. 2C

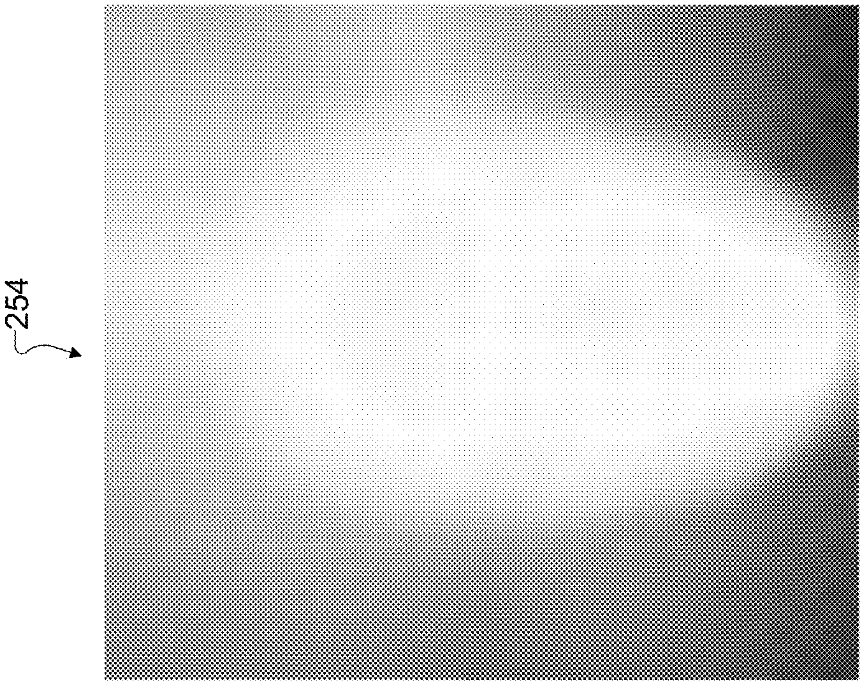


FIG. 2D

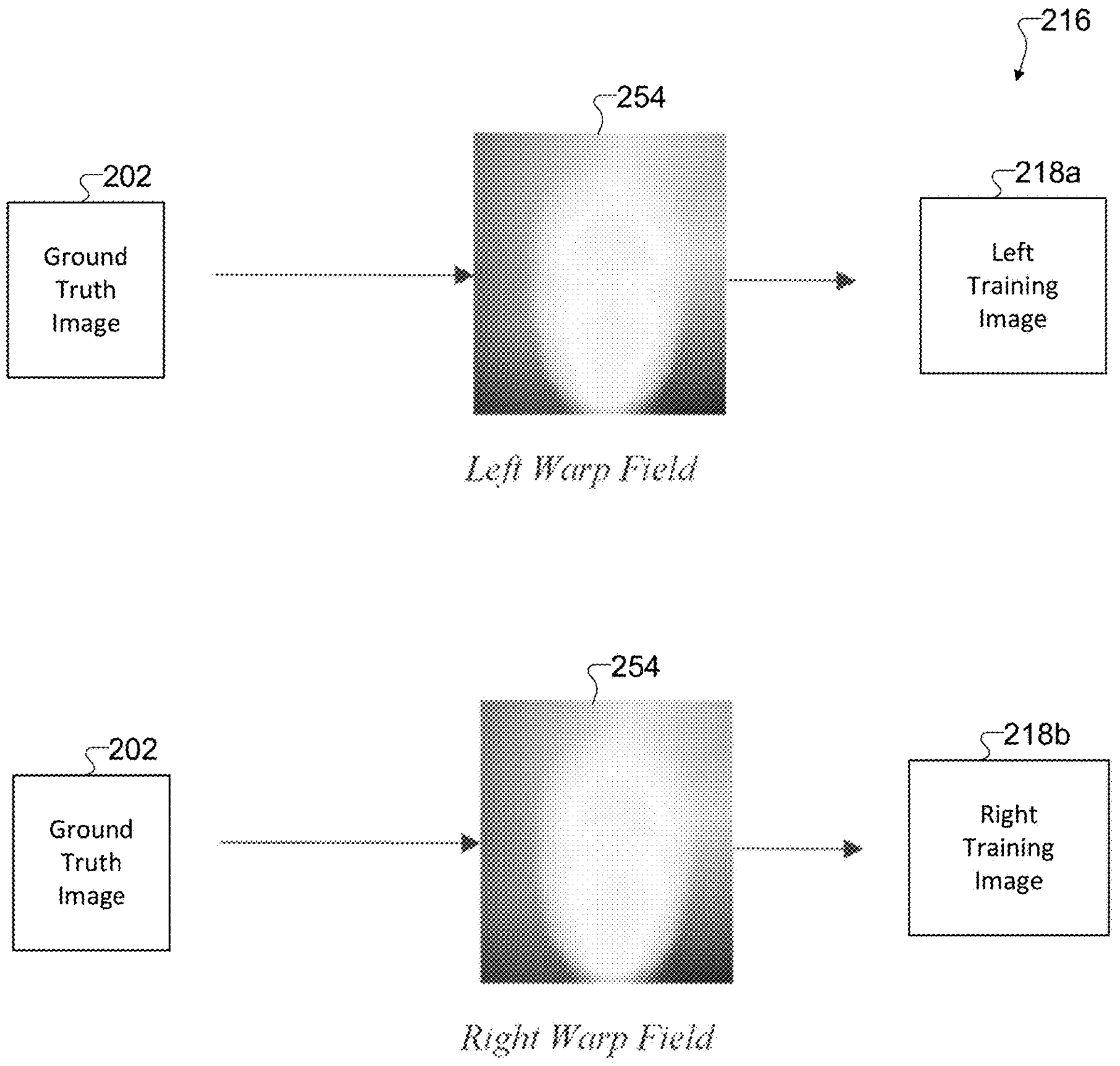

216
202
Ground Truth Image
254
Left Warp Field
218a
Left Training Image
202
Ground Truth Image
254
Right Warp Field
218b
Right Training Image

FIG. 2E

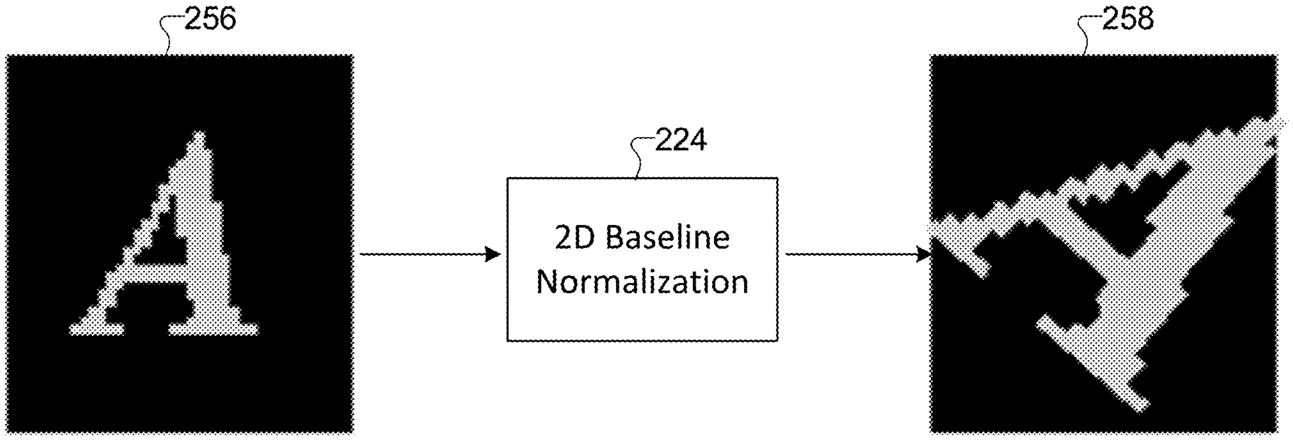


FIG. 2F

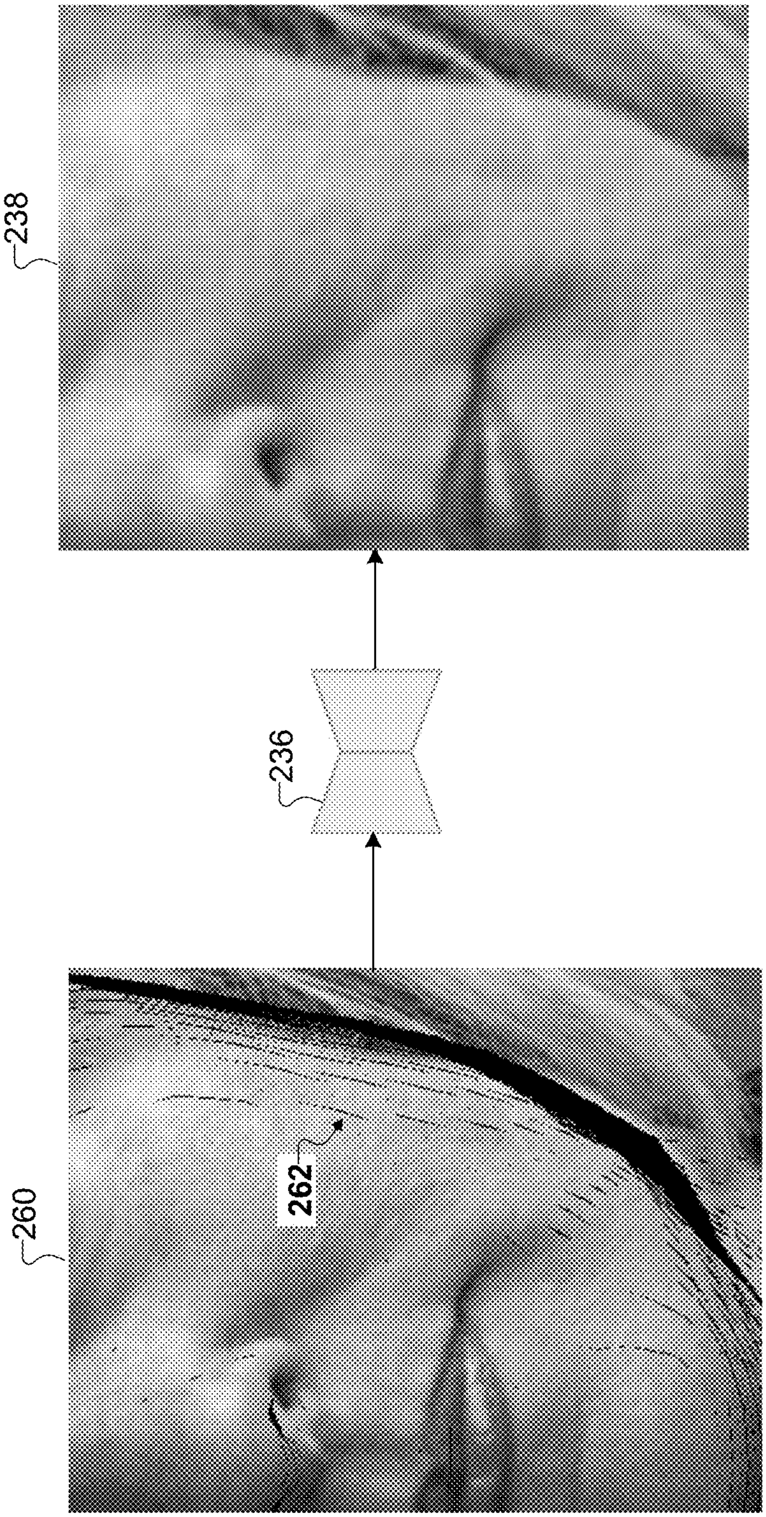


FIG. 2G

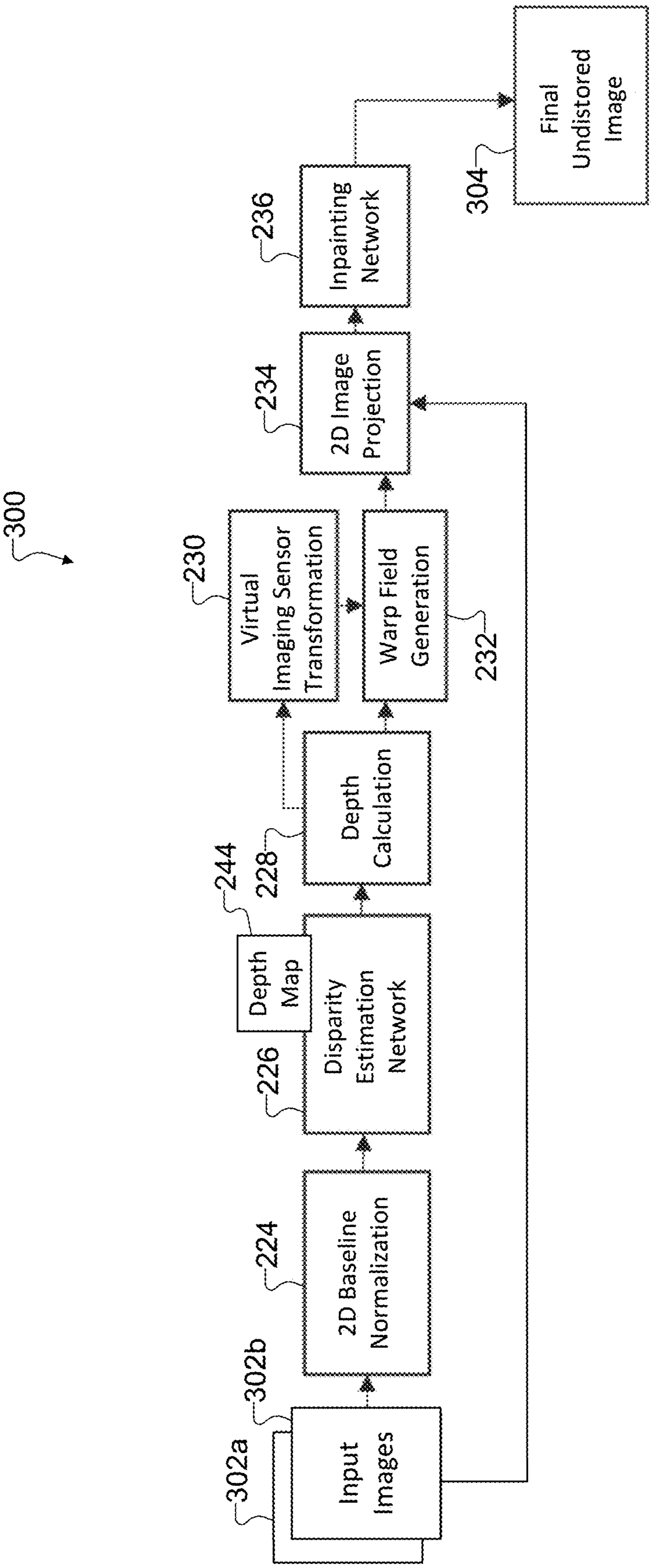
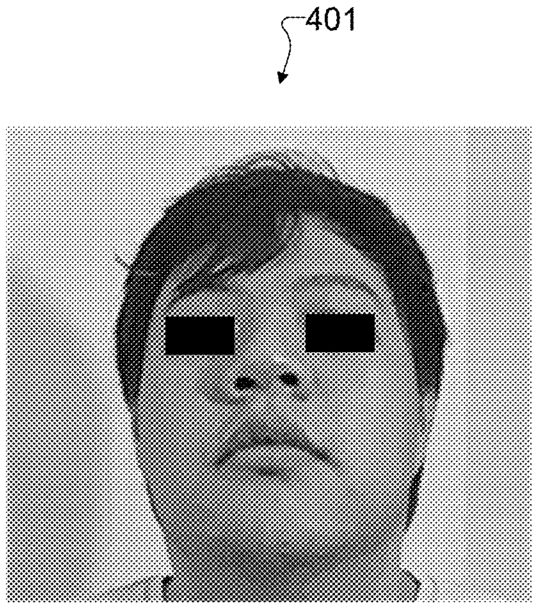

300
Input Images
302a
302b
2D Baseline Normalization
224
Disparity Estimation Network
226
Depth Map
244
Depth Calculation
228
Virtual Imaging Sensor Transformation
230
Warp Field Generation
232
2D Image Projection
234
Inpainting Network
236
Final Undistored Image
304

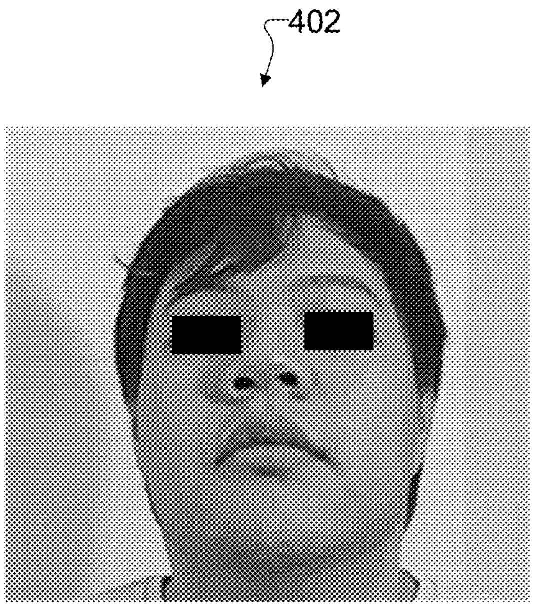
FIG. 3



[redacted] [redacted]

Left image

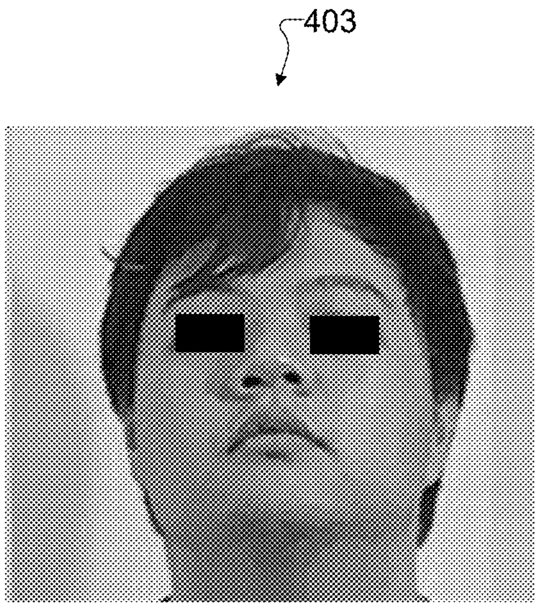
FIG. 4A



[redacted] [redacted]

Right image

FIG. 4B



[redacted] [redacted]

Results

FIG. 4C

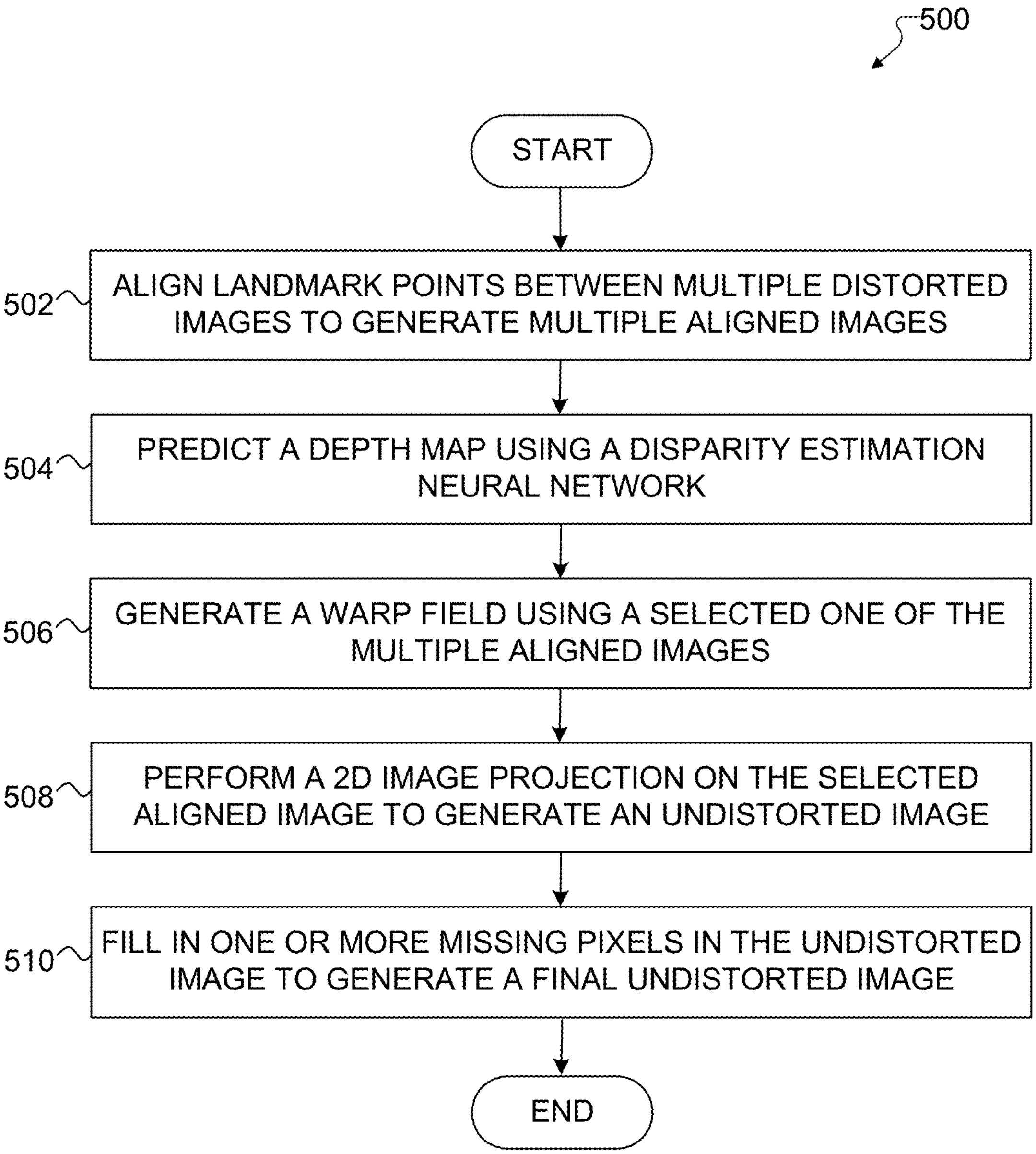

500
START
502
ALIGN LANDMARK POINTS BETWEEN MULTIPLE DISTORTED IMAGES TO GENERATE MULTIPLE ALIGNED IMAGES
504
PREDICT A DEPTH MAP USING A DISPARITY ESTIMATION NEURAL NETWORK
506
GENERATE A WARP FIELD USING A SELECTED ONE OF THE MULTIPLE ALIGNED IMAGES
508
PERFORM A 2D IMAGE PROJECTION ON THE SELECTED ALIGNED IMAGE TO GENERATE AN UNDISTORTED IMAGE
510
FILL IN ONE OR MORE MISSING PIXELS IN THE UNDISTORTED IMAGE TO GENERATE A FINAL UNDISTORTED IMAGE
END

FIG. 5

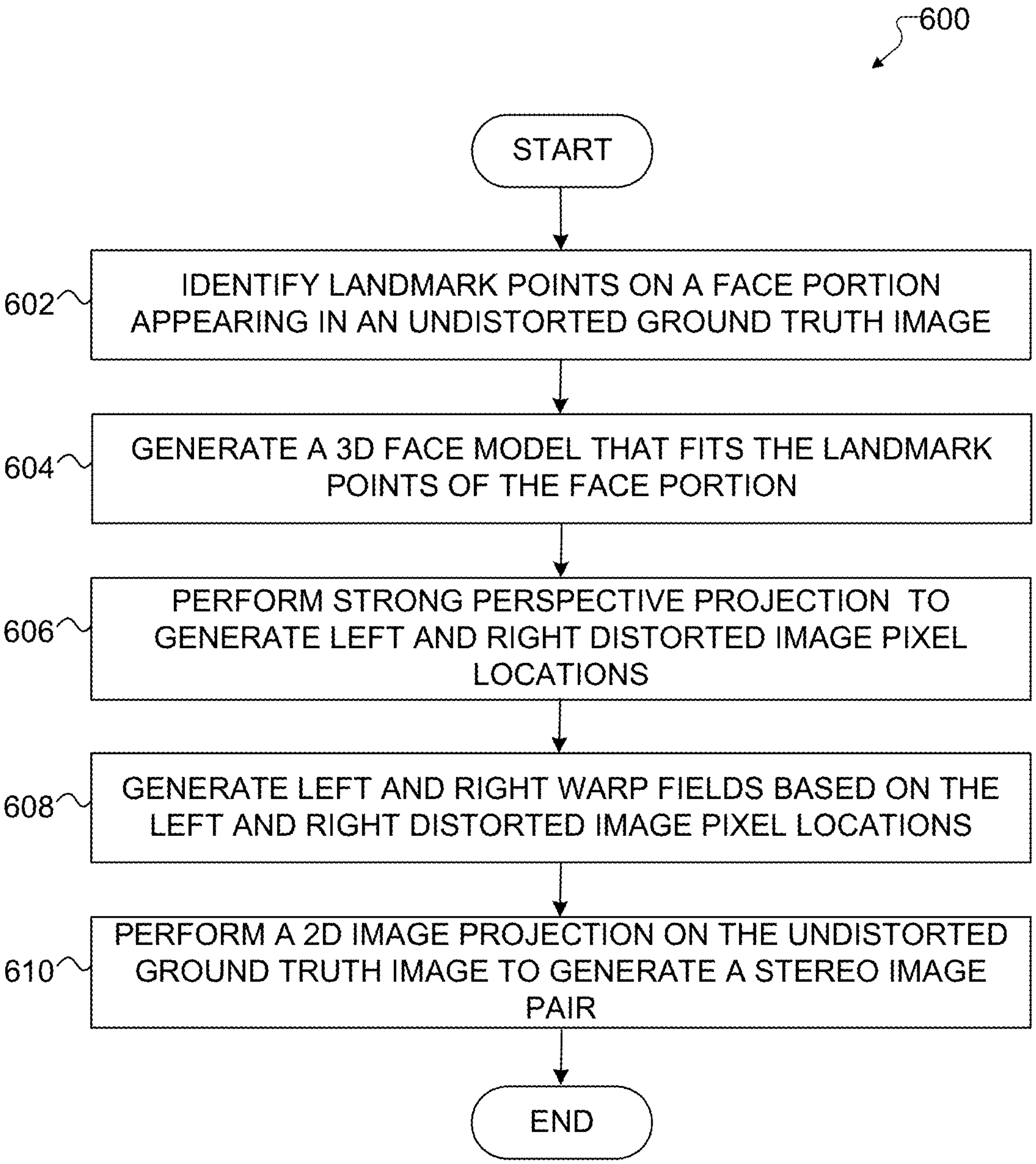

600
START
602
IDENTIFY LANDMARK POINTS ON A FACE PORTION APPEARING IN AN UNDISTORTED GROUND TRUTH IMAGE
604
GENERATE A 3D FACE MODEL THAT FITS THE LANDMARK POINTS OF THE FACE PORTION
606
PERFORM STRONG PERSPECTIVE PROJECTION TO GENERATE LEFT AND RIGHT DISTORTED IMAGE PIXEL LOCATIONS
608
GENERATE LEFT AND RIGHT WARP FIELDS BASED ON THE LEFT AND RIGHT DISTORTED IMAGE PIXEL LOCATIONS
610
PERFORM A 2D IMAGE PROJECTION ON THE UNDISTORTED GROUND TRUTH IMAGE TO GENERATE A STEREO IMAGE PAIR
END

FIG. 6

SYSTEM AND METHOD FOR FACIAL UN-DISTORTION IN DIGITAL IMAGES USING MULTIPLE IMAGING SENSORS

TECHNICAL FIELD

This disclosure relates generally to imaging systems. More specifically, this disclosure relates to a system and method for facial un-distortion in digital images using multiple imaging sensors.

BACKGROUND

With the recent developments in mobile device camera technology, it has become common for mobile device users to take "selfies." Since, by definition, a selfie is an image of the user taken by the user, selfie photos are commonly taken at an arm-length distance. This small distance can result in perspective distortion of a face that appear in the selfie. For example, in many selfies, the face appears narrower and the nose is enlarged compared to the actual face. Perspective distortion of faces can result in unappealing facial appearances in selfies. This can also result in unsatisfactory user experience, both in capturing selfies and during handheld video calls.

SUMMARY

This disclosure provides a system and method for facial un-distortion in digital images using multiple imaging sensors.

In a first embodiment, a method includes aligning landmark points between multiple distorted images to generate multiple aligned images, where the multiple distorted images exhibit perspective distortion in at least one face appearing in the multiple distorted images. The method also includes predicting a depth map using a disparity estimation neural network that receives the multiple aligned images as input. The method further includes generating a warp field using a selected one of the multiple aligned images. The method also includes performing a two-dimensional (2D) image projection on the selected aligned image using the depth map and the warp field to generate an undistorted image. In addition, the method includes filling in one or more missing pixels in the undistorted image using an inpainting neural network to generate a final undistorted image.

In a second embodiment, an electronic device includes at least one memory configured to store instructions. The electronic device also includes at least one processing device configured when executing the instructions to align landmark points between multiple distorted images to generate multiple aligned images, where the multiple distorted images exhibit perspective distortion in at least one face appearing in the multiple distorted images. The at least one processing device is also configured when executing the instructions to predict a depth map using a disparity estimation neural network that receives the multiple aligned images as input. The at least one processing device is further configured when executing the instructions to generate a warp field using a selected one of the multiple aligned images. The at least one processing device is also configured when executing the instructions to perform a 2D image projection on the selected aligned image using the depth map and the warp field to generate an undistorted image. In addition, the at least one processing device is configured when executing the instructions to fill in one or more missing pixels in the undistorted image using an inpainting neural network to generate a final undistorted image.

In a third embodiment, a non-transitory machine-readable medium contains instructions that when executed cause at least one processor of an electronic device to align landmark points between multiple distorted images to generate multiple aligned images, where the multiple distorted images exhibit perspective distortion in at least one face appearing in the multiple distorted images. The medium also contains instructions that when executed cause the at least one processor to predict a depth map using a disparity estimation neural network that receives the multiple aligned images as input. The medium further contains instructions that when executed cause the at least one processor to generate a warp field using a selected one of the multiple aligned images. The medium also contains instructions that when executed cause the at least one processor to perform a 2D image projection on the selected aligned image using the depth map and the warp field to generate an undistorted image. In addition, the medium contains instructions that when executed cause the at least one processor to fill in one or more missing pixels in the undistorted image using an inpainting neural network to generate a final undistorted image.

In a fourth embodiment, a method includes identifying landmark points on a face portion of a person appearing in an undistorted ground truth image. The method also includes generating a three-dimensional (3D) face model that fits the landmark points of the face portion, where the 3D face model includes depth information of the face portion. The method further includes performing a perspective projection using the undistorted ground truth image and the depth information of the face portion to generate left and right distorted image pixel locations. The method also includes generating left and right warp fields based on the left and right distorted image pixel locations. In addition, the method includes performing a 2D image projection on the undistorted ground truth image using the 3D face model and the left and right warp fields to generate a stereo image pair.

Other technical features may be readily apparent to one skilled in the art from the following figures, descriptions, and claims.

Before undertaking the DETAILED DESCRIPTION below, it may be advantageous to set forth definitions of certain words and phrases used throughout this patent document. The terms "transmit," "receive," and "communicate," as well as derivatives thereof, encompass both direct and indirect communication. The terms "include" and "comprise," as well as derivatives thereof, mean inclusion without limitation. The term "or" is inclusive, meaning and/or. The phrase "associated with," as well as derivatives thereof, means to include, be included within, interconnect with, contain, be contained within, connect to or with, couple to or with, be communicable with, cooperate with, interleave, juxtapose, be proximate to, be bound to or with, have, have a property of, have a relationship to or with, or the like.

Moreover, various functions described below can be implemented or supported by one or more computer programs, each of which is formed from computer readable program code and embodied in a computer readable medium. The terms "application" and "program" refer to one or more computer programs, software components, sets of instructions, procedures, functions, objects, classes, instances, related data, or a portion thereof adapted for implementation in a suitable computer readable program code. The phrase "computer readable program code" includes any type of computer code, including source code, object code, and executable code. The phrase "computer readable medium" includes any type of medium capable of being accessed by a computer, such as read only memory (ROM), random access memory (RAM), a hard disk drive, a compact disc (CD), a digital video disc (DVD), or any other type of memory. A "non-transitory" computer readable medium excludes wired, wireless, optical, or other communication links that transport transitory electrical or other signals. A non-transitory computer readable medium includes media where data can be permanently stored and media where data can be stored and later overwritten, such as a rewritable optical disc or an erasable memory device.

As used here, terms and phrases such as "have," "may have," "include," or "may include" a feature (like a number, function, operation, or component such as a part) indicate the existence of the feature and do not exclude the existence of other features. Also, as used here, the phrases "A or B," "at least one of A and/or B," or "one or more of A and/or B" may include all possible combinations of A and B. For example, "A or B," "at least one of A and B," and "at least one of A or B" may indicate all of (1) including at least one A, (2) including at least one B, or (3) including at least one A and at least one B. Further, as used here, the terms "first" and "second" may modify various components regardless of importance and do not limit the components. These terms are only used to distinguish one component from another. For example, a first user device and a second user device may indicate different user devices from each other, regardless of the order or importance of the devices. A first component may be denoted a second component and vice versa without departing from the scope of this disclosure.

It will be understood that, when an element (such as a first element) is referred to as being (operatively or communicatively) "coupled with/to" or "connected with/to" another element (such as a second element), it can be coupled or connected with/to the other element directly or via a third element. In contrast, it will be understood that, when an element (such as a first element) is referred to as being "directly coupled with/to" or "directly connected with/to" another element (such as a second element), no other element (such as a third element) intervenes between the element and the other element.

As used here, the phrase "configured (or set) to" may be interchangeably used with the phrases "suitable for," "having the capacity to," "designed to," "adapted to," "made to," or "capable of" depending on the circumstances. The phrase "configured (or set) to" does not essentially mean "specifically designed in hardware to." Rather, the phrase "configured to" may mean that a device can perform an operation together with another device or parts. For example, the phrase "processor configured (or set) to perform A, B, and C" may mean a generic-purpose processor (such as a CPU or application processor) that may perform the operations by executing one or more software programs stored in a memory device or a dedicated processor (such as an embedded processor) for performing the operations.

The terms and phrases as used here are provided merely to describe some embodiments of this disclosure but not to limit the scope of other embodiments of this disclosure. It is to be understood that the singular forms "a," "an," and "the" include plural references unless the context clearly dictates otherwise. All terms and phrases, including technical and scientific terms and phrases, used here have the same meanings as commonly understood by one of ordinary skill in the art to which the embodiments of this disclosure belong. It will be further understood that terms and phrases, such as those defined in commonly-used dictionaries, should be interpreted as having a meaning that is consistent with their meaning in the context of the relevant art and will not be interpreted in an idealized or overly formal sense unless expressly so defined here. In some cases, the terms and phrases defined here may be interpreted to exclude embodiments of this disclosure.

Examples of an "electronic device" according to embodiments of this disclosure may include at least one of a smartphone, a tablet personal computer (PC), a mobile phone, a video phone, an e-book reader, a desktop PC, a laptop computer, a netbook computer, a workstation, a personal digital assistant (PDA), a portable multimedia player (PMP), an MP3 player, a mobile medical device, a camera, or a wearable device (such as smart glasses, a head-mounted device (HMD), electronic clothes, an electronic bracelet, an electronic necklace, an electronic accessory, an electronic tattoo, a smart mirror, or a smart watch). Other examples of an electronic device include a smart home appliance. Examples of the smart home appliance may include at least one of a television, a digital video disc (DVD) player, an audio player, a refrigerator, an air conditioner, a cleaner, an oven, a microwave oven, a washer, a drier, an air cleaner, a set-top box, a home automation control panel, a security control panel, a TV box (such as SAMSUNG HOMESYNC, APPLETV, or GOOGLE TV), a smart speaker or speaker with an integrated digital assistant (such as SAMSUNG GALAXY HOME, APPLE HOMEPOD, or AMAZON ECHO), a gaming console (such as an XBOX, PLAYSTATION, or NINTENDO), an electronic dictionary, an electronic key, a camcorder, or an electronic picture frame. Still other examples of an electronic device include at least one of various medical devices (such as diverse portable medical measuring devices (like a blood sugar measuring device, a heartbeat measuring device, or a body temperature measuring device), a magnetic resource angiography (MRA) device, a magnetic resource imaging (MRI) device, a computed tomography (CT) device, an imaging device, or an ultrasonic device), a navigation device, a global positioning system (GPS) receiver, an event data recorder (EDR), a flight data recorder (FDR), an automotive infotainment device, a sailing electronic device (such as a sailing navigation device or a gyro compass), avionics, security devices, vehicular head units, industrial or home robots, automatic teller machines (ATMs), point of sales (POS) devices, or Internet of Things (IoT) devices (such as a bulb, various sensors, electric or gas meter, sprinkler, fire alarm, thermostat, street light, toaster, fitness equipment, hot water tank, heater, or boiler). Other examples of an electronic device include at least one part of a piece of furniture or building/structure, an electronic board, an electronic signature receiving device, a projector, or various measurement devices (such as devices for measuring water, electricity, gas, or electromagnetic waves). Note that, according to various embodiments of this disclosure, an electronic device may be one or a combination of the above-listed devices. According to some embodiments of this disclosure, the electronic device may be a flexible electronic device. The electronic device disclosed here is not limited to the above-listed devices and may include new electronic devices depending on the development of technology.

In the following description, electronic devices are described with reference to the accompanying drawings, according to various embodiments of this disclosure. As used here, the term "user" may denote a human or another device (such as an artificial intelligent electronic device) using the electronic device.

Definitions for other certain words and phrases may be provided throughout this patent document. Those of ordinary skill in the art should understand that in many if not most instances, such definitions apply to prior as well as future uses of such defined words and phrases.

None of the description in this application should be read as implying that any particular element, step, or function is an essential element that must be included in the claim scope. The scope of patented subject matter is defined only by the claims. Moreover, none of the claims is intended to invoke 35 U.S.C. § 112(f) unless the exact words "means for" are followed by a participle. Use of any other term, including without limitation "mechanism," "module," "device," "unit," "component," "element," "member," "apparatus," "machine," "system," "processor," or "controller," within a claim is understood by the Applicant to refer to structures known to those skilled in the relevant art and is not intended to invoke 35 U.S.C. § 112(f).

BRIEF DESCRIPTION OF THE DRAWINGS

For a more complete understanding of this disclosure and its advantages, reference is now made to the following description taken in conjunction with the accompanying drawings, in which like reference numerals represent like parts:

FIG. **1** illustrates an example network configuration including an electronic device according to this disclosure;

FIGS. **2**A through **2**G illustrate an example training framework for facial un-distortion in digital images using multiple imaging sensors according to this disclosure;

FIG. **3** illustrates an example process for facial un-distortion in digital images using multiple imaging sensors according to this disclosure;

FIGS. **4**A through **4**C illustrate examples of benefits that can be realized using one or more of the embodiments of this disclosure;

FIG. **5** illustrates an example method for facial un-distortion in digital images using multiple imaging sensors according to this disclosure; and

FIG. **6** illustrates an example method for generating and using training data according to this disclosure.

DETAILED DESCRIPTION

FIGS. **1** through **6**, discussed below, and the various embodiments of this disclosure are described with reference to the accompanying drawings. However, it should be appreciated that this disclosure is not limited to these embodiments and all changes and/or equivalents or replacements thereto also belong to the scope of this disclosure.

As discussed above, with the recent developments in mobile device camera technology, it has become common for mobile device users to take "selfies." Since, by definition, a selfie is an image of the user taken by the user, selfie photos are commonly taken at an arm-length distance. This small distance can result in perspective distortion of a face that appear in the selfie. For example, in many selfies, the face appears narrower and the nose is enlarged compared to the actual face. Here, perspective distortion is distinguished from other types of image distortion, such as caused by sensor noise or malfunction. Perspective distortion of faces can result in unappealing facial appearances in selfies. This can also result in unsatisfactory user experience, both in capturing selfies and during handheld video calls. Some techniques have been developed to fix perspective distortion in selfies. However, these techniques are implemented post-capture and require a depth map of the subject. These techniques therefore require additional complicated algorithms and/or depth sensors, both of which add complexity to a smartphone or other mobile device.

This disclosure provides systems and methods for facial un-distortion in digital images using multiple imaging sensors. As described in more detail below, the disclosed systems and methods receive a distorted pair of images captured with multiple imaging sensors and correct perspective distortion of human faces in the images without the use of a pre-generated depth map. In some embodiments, the disclosed systems and methods use an end-to-end differentiable deep learning pipeline to correct the perspective distortion. In addition, the disclosed systems and methods allow for variable distance between the multiple imaging sensors, as well as variable focal lengths and sensor gains. Compared to prior techniques, the disclosed embodiments achieve significant improvement in facial distortion correction without requiring the use of a depth sensor. Note that while some of the embodiments discussed below are described in the context of use in consumer electronic devices, such as smartphones or tablet computers, this are merely examples. It will be understood that the principles of this disclosure may be implemented in any number of other suitable contexts.

FIG. **1** illustrates an example network configuration **100** including an electronic device according to this disclosure. The embodiment of the network configuration **100** shown in FIG. **1** is for illustration only. Other embodiments of the network configuration **100** could be used without departing from the scope of this disclosure.

According to embodiments of this disclosure, an electronic device **101** is included in the network configuration **100**. The electronic device **101** can include at least one of a bus **110**, a processor **120**, a memory **130**, an input/output (I/O) interface **150**, a display **160**, a communication interface **170**, or a sensor **180**. In some embodiments, the electronic device **101** may exclude at least one of these components or may add at least one other component. The bus **110** includes a circuit for connecting the components **120-180** with one another and for transferring communications (such as control messages and/or data) between the components.

The processor **120** includes one or more of a central processing unit (CPU), an application processor (AP), or a communication processor (CP). The processor **120** is able to perform control on at least one of the other components of the electronic device **101** and/or perform an operation or data processing relating to communication. In some embodiments, the processor **120** can be a graphics processor unit (GPU). As described in more detail below, the processor **120** may perform one or more operations for facial un-distortion in digital images using multiple cameras or other imaging sensors.

The memory **130** can include a volatile and/or non-volatile memory. For example, the memory **130** can store commands or data related to at least one other component of the electronic device **101**. According to embodiments of this disclosure, the memory **130** can store software and/or a program **140**. The program **140** includes, for example, a kernel **141**, middleware **143**, an application programming interface (API) **145**, and/or an application program (or "application") **147**. At least a portion of the kernel **141**, middleware **143**, or API **145** may be denoted an operating system (OS).

The kernel **141** can control or manage system resources (such as the bus **110**, processor **120**, or memory **130**) used to perform operations or functions implemented in other programs (such as the middleware **143**, API **145**, or application **147**). The kernel **141** provides an interface that allows the middleware **143**, the API **145**, or the application **147** to access the individual components of the electronic device **101** to control or manage the system resources. The application **147** may support one or more functions for facial un-distortion in digital images using multiple cameras or other imaging sensors as discussed below. These functions can be performed by a single application or by multiple applications that each carry out one or more of these functions. The middleware **143** can function as a relay to allow the API **145** or the application **147** to communicate data with the kernel **141**, for instance. A plurality of applications **147** can be provided. The middleware **143** is able to control work requests received from the applications **147**, such as by allocating the priority of using the system resources of the electronic device **101** (like the bus **110**, the processor **120**, or the memory **130**) to at least one of the plurality of applications **147**. The API **145** is an interface allowing the application **147** to control functions provided from the kernel **141** or the middleware **143**. For example, the API **145** includes at least one interface or function (such as a command) for filing control, window control, image processing, or text control.

The I/O interface **150** serves as an interface that can, for example, transfer commands or data input from a user or other external devices to other component(s) of the electronic device **101**. The I/O interface **150** can also output commands or data received from other component(s) of the electronic device **101** to the user or the other external device.

The display **160** includes, for example, a liquid crystal display (LCD), a light emitting diode (LED) display, an organic light emitting diode (OLED) display, a quantum-dot light emitting diode (QLED) display, a microelectromechanical systems (MEMS) display, or an electronic paper display. The display **160** can also be a depth-aware display, such as a multi-focal display. The display **160** is able to display, for example, various contents (such as text, images, videos, icons, or symbols) to the user. The display **160** can include a touchscreen and may receive, for example, a touch, gesture, proximity, or hovering input using an electronic pen or a body portion of the user.

The communication interface **170**, for example, is able to set up communication between the electronic device **101** and an external electronic device (such as a first electronic device **102**, a second electronic device **104**, or a server **106**). For example, the communication interface **170** can be connected with a network **162** or **164** through wireless or wired communication to communicate with the external electronic device. The communication interface **170** can be a wired or wireless transceiver or any other component for transmitting and receiving signals.

The wireless communication is able to use at least one of, for example, long term evolution (LTE), long term evolution-advanced (LTE-A), 5th generation wireless system (5G), millimeter-wave or 60 GHz wireless communication, Wireless USB, code division multiple access (CDMA), wideband code division multiple access (WCDMA), universal mobile telecommunication system (UMTS), wireless broadband (WiBro), or global system for mobile communication (GSM), as a cellular communication protocol. The wired connection can include, for example, at least one of a universal serial bus (USB), high definition multimedia interface (HDMI), recommended standard 232 (RS-232), or plain old telephone service (POTS). The network **162** or **164** includes at least one communication network, such as a computer network (like a local area network (LAN) or wide area network (WAN)), Internet, or a telephone network.

The electronic device **101** further includes one or more sensors **180** that can meter a physical quantity or detect an activation state of the electronic device **101** and convert metered or detected information into an electrical signal. For example, one or more sensors **180** include one or more cameras or other imaging sensors for capturing images of scenes. The sensor(s) **180** can also include one or more buttons for touch input, a gesture sensor, a gyroscope or gyro sensor, an air pressure sensor, a magnetic sensor or magnetometer, an acceleration sensor or accelerometer, a grip sensor, a proximity sensor, a color sensor (such as a red green blue (RGB) sensor), a bio-physical sensor, a temperature sensor, a humidity sensor, an illumination sensor, an ultraviolet (UV) sensor, an electromyography (EMG) sensor, an electroencephalogram (EEG) sensor, an electrocardiogram (ECG) sensor, an infrared (IR) sensor, an ultrasound sensor, an iris sensor, or a fingerprint sensor. The sensor(s) **180** can further include an inertial measurement unit, which can include one or more accelerometers, gyroscopes, and other components. In addition, the sensor(s) **180** can include a control circuit for controlling at least one of the sensors included here. Any of these sensor(s) **180** can be located within the electronic device **101**.

The first external electronic device **102** or the second external electronic device **104** can be a wearable device or an electronic device-mountable wearable device (such as an HMD). When the electronic device **101** is mounted in the electronic device **102** (such as the HMD), the electronic device **101** can communicate with the electronic device **102** through the communication interface **170**. The electronic device **101** can be directly connected with the electronic device **102** to communicate with the electronic device **102** without involving with a separate network. The electronic device **101** can also be an augmented reality wearable device, such as eyeglasses, that include one or more imaging sensors.

The first and second external electronic devices **102** and **104** and the server **106** each can be a device of the same or a different type from the electronic device **101**. According to certain embodiments of this disclosure, the server **106** includes a group of one or more servers. Also, according to certain embodiments of this disclosure, all or some of the operations executed on the electronic device **101** can be executed on another or multiple other electronic devices (such as the electronic devices **102** and **104** or server **106**). Further, according to certain embodiments of this disclosure, when the electronic device **101** should perform some function or service automatically or at a request, the electronic device **101**, instead of executing the function or service on its own or additionally, can request another device (such as electronic devices **102** and **104** or server **106**) to perform at least some functions associated therewith. The other electronic device (such as electronic devices **102** and **104** or server **106**) is able to execute the requested functions or additional functions and transfer a result of the execution to the electronic device **101**. The electronic device **101** can provide a requested function or service by processing the received result as it is or additionally. To that end, a cloud computing, distributed computing, or client-server computing technique may be used, for example. While FIG. **1** shows that the electronic device **101** includes the communication interface **170** to communicate with the external electronic device **104** or server **106** via the network **162** or **164**, the electronic device **101** may be independently operated without a separate communication function according to some embodiments of this disclosure.

The server **106** can include the same or similar components **110-180** as the electronic device **101** (or a suitable subset thereof). The server **106** can support to drive the electronic device **101** by performing at least one of operations (or functions) implemented on the electronic device **101**. For example, the server **106** can include a processing module or processor that may support the processor **120** implemented in the electronic device **101**. As described in more detail below, the server **106** may perform one or more operations to support techniques for facial un-distortion in digital images using multiple cameras or other imaging sensors.

Although FIG. **1** illustrates one example of a network configuration **100** including an electronic device **101**, various changes may be made to FIG. **1**. For example, the network configuration **100** could include any number of each component in any suitable arrangement. In general, computing and communication systems come in a wide variety of configurations, and FIG. **1** does not limit the scope of this disclosure to any particular configuration. Also, while FIG. **1** illustrates one operational environment in which various features disclosed in this patent document can be used, these features could be used in any other suitable system.

FIGS. **2**A through **2**G illustrate an example training framework **200** for facial un-distortion in digital images using multiple imaging sensors according to this disclosure. For ease of explanation, the framework **200** is described as being implemented using one or more components of the electronic device **101** described above. However, this is merely one example, and the framework **200** could be implemented using any other suitable device(s), such as when implemented using the server **106**.

As shown in FIG. **2**A, the framework **200** includes a training data generation process **220** and a training process **240**. As described in greater detail below, the training data generation process **220** is performed to generate training data (in the form of training stereo pairs **218***a*-**218***b*) that can be used in the training process **240**. The framework **200** provides a number of advantages or benefits over prior training techniques. Correction of perspective distortion typically requires a depth map of the face, but the framework **200** does not require a depth map as an input. Existing depth map techniques do not provide sufficient resolution on the face area. For example, such depth maps may not provide a clear indication where certain facial elements (such as eyes, nose, ears, chin, and the like) are located. Thus, it is difficult to correct for facial distortions using these depth maps. As described in greater detail below, the framework **200** generates suitable depth maps that can used in the training process **240**.

Starting with the training data generation process **220**, the electronic device **101** obtains at least one ground truth image **202**. The ground truth image **202** represents a "clean" image of a person's face that includes no distortion. Each ground truth image **202** can be obtained in any suitable manner. For example, the electronic device **101** can obtain the ground truth image **202** from an image database. Using the ground truth image **202** as an input, the electronic device **101** performs a two-dimensional (2D) landmark detection process **204** to identify specific landmarks (such as eyes, nose, nostrils, corners of lips, a contour of a jaw line, and the like) on the face shown in the ground truth image **202**.

FIG. **2**B illustrates an example of the 2D landmark detection process **204**. As shown in FIG. **2**B, using the 2D landmark detection process **204**, the electronic device **101** obtains a set of key points, referred to as landmark points **250**, on the ground truth image **202**. The landmark points **250** can correspond to a pre-defined set of locations that are used in fitting a face model to the ground truth image **202**. As shown in FIG. **2**B, the landmark points **250** can include locations such as eyebrows, eye corners, lip corners, a chin contour, and the like. The 2D landmark detection process **204** represents any suitable landmark detection technique, including learning- or non-learning-based techniques. In some cases, the 2D landmark detection process **204** can be expressed mathematically as follows:

$$\Phi:I\rightarrow\{(x_1,y_1),(x_2,y_2),\ldots(x_L,y_L)\} \tag{1}$$

where Φ represents the 2D landmark detection process **204**, I represents the ground truth image **202**, and (x_L, y_L) represents each of the landmark points **250**.

Using the set of landmark points **250** as an input, the electronic device **101** performs a weak perspective three-dimensional (3D) face model fitting process **206** to generate a 3D model of the face in the ground truth image **202**, where the 3D model can explain the landmark points **250**. Here, a weak perspective model represents use of a virtual camera or other virtual imaging sensor that is relatively far away from the subject, thereby having weaker perspective distortion (as compared to a relatively close virtual imaging sensor, which would generate a stronger perspective distortion). FIG. **2**C illustrates additional details of an example weak perspective 3D face model fitting process **206**. As shown in FIG. **2**C, a face model **252** is a 3D projection obtained using the weak perspective 3D face model fitting process **206**. The point C represents the optical center of the camera system which is used to measure the distance of the subject from the camera. The parameter Z_{avg} represents the average distance of the subject from the optical center of the camera system.

The 3D model **252** can be represented by a set of face model parameters, which are obtained by projecting corresponding landmark points of the 3D model **252** onto the face portion of the ground truth image **202** and minimizing the distance between the landmark points **250** and the projected landmark points of the 3D model **252**. In projecting the landmark points from the 3D model to the 2D image plane, the weak perspective 3D face model fitting process **206** assumes a large distance between the subject and the imaging sensor. That is, a weak perspective model is assumed because the ground truth image **202** is distortion free, so it is assumed that the ground truth image **202** is obtained at a large distance. Thus, the relative depths of facial features are negligible compared with the imaging sensor-to-subject distance. The projection of each landmark point **250** can be represented by the following:

$$x=\frac{X}{Z_{avg}},\ y=\frac{Y}{Z_{avg}} \tag{2}$$

where X and Y represent coordinates of landmark points on the 3D model **252**, and Z_{avg} represent the average subject-to-imaging sensor distance. It is noted that Z_{avg} is a constant and is much larger than the values of X and Y. For example, in some embodiments, Z_{avg} is at least one hundred times larger than the values of X and Y, although other multiples are possible. It is also noted that for the purposes of mathematical simplicity and without loss of generality, the focal length is assumed to be equal to a constant value of 1 (in any units which are being used).

The weak perspective 3D face model fitting process **206** represents any suitable technique for generating a 3D model of a face from a given input image under the assumption that the camera to subject distance is large. In some embodiments, the weak perspective 3D face model fitting process **206** uses a FLAME model technique to generate the 3D model, although other techniques are possible and within the scope of this disclosure.

After the weak perspective 3D face model fitting process **206**, the electronic device **101** performs a weak-to-strong perspective transformation process **208**, which simulates moving the virtual imaging sensor closer to the subject. The electronic device **101** also reprojects all the pixels of the input ground truth image using their depth information from the fitted 3D model **252**, thereby generating a stronger perspective distortion model (since perspective distortion is stronger at closer distances). Using the weak-to-strong perspective transformation process **208**, the electronic device **101** obtains new pixel locations for a distorted image that has the appearance of being captured from a short distance. In some embodiments, the electronic device **101** uses a strong perspective model that can be represented by the following (assuming a focal length of 1):

$$x' = \frac{X}{Z},\ y' = \frac{Y}{Z} \tag{3}$$

where X, Y, Z represent the 3D locations of the landmark points on the 3D model **252** with respect to the camera optical center (origin) C, and (x', y') represent new 2D locations of the pixels in the distorted image. In Equation (3), the denominator Z is variable and can change for each landmark point. The values of Z may be much less than the value of Z_{avg} in Equation (2) because the virtual imaging sensor has been moved much closer to the subject.

In some cases, the calculations using Equation (3) can be performed twice in the weak-to-strong perspective transformation process **208**, once for each distorted image of a training stereo pair **218***a*-**218***b*. As discussed in greater detail below, each image of the training stereo pair **218***a*-**218***b* represents an image taken from a different imaging sensor of an electronic device, such as a dual imaging sensor smartphone or other electronic device having a left imaging sensor and a right imaging sensor. Each imaging sensor inherently has a different origin C as shown in FIG. **2**C since the imaging sensors are disposed at different positions on the electronic device.

After the weak-to-strong perspective transformation process **208**, the electronic device **101** performs a virtual imaging sensor transformation process **210** and a depth calculation process **212**. The virtual imaging sensor transformation process **210** is performed to obtain new distance values for the distorted images using the depth values from the 3D model **252**. The electronic device **101** can perform any suitable virtual imaging sensor transformation process **210**. The depth calculation process **212** is performed to convert distance units of the depth values (such as meters, centimeters, inches, or the like) into pixels.

After the depth calculation process **212**, the electronic device **101** performs a warp field generation process **214** to generate warp fields corresponding to the left and right imaging sensors. FIG. **2**D illustrates an example of a warp field **254** generated by the warp field generation process **214**. As shown in FIG. **2**D, the warp field **254** represents a 2D-to-2D mapping of pixels between the undistorted ground truth image **202** and the distorted images obtained in the weak-to-strong perspective transformation process **208**. In the warp field generation process **214**, the electronic device **101** may generate each warp field **254** by calculating the difference between undistorted pixel locations (x, y) obtained in the weak perspective 3D face model fitting process **206** and the distorted pixel locations (x', y') obtained in the weak-to-strong perspective transformation process **208**. Mathematically, this can be expressed as obtaining a difference vector d for each pixel location as follows.

$$d = \begin{bmatrix} x' - x \\ y' - y \end{bmatrix} \tag{4}$$

The difference vector d can be used to obtain the new location of a pixel in the distorted image plane. In the warp field generation process **214**, the electronic device **101** computes a left warp field **254** corresponding to the left imaging sensor and a right warp field **254** corresponding to the right imaging sensor. Each warp field **254** can be based on a different origin C as shown in FIG. **2**C since the left and right imaging sensors are disposed at different positions.

After the electronic device **101** generates the warp fields **254**, the electronic device **101** performs a 2D image projection process **216** on the ground truth image **202** to generate a training stereo pair **218***a*-**218***b*, which are the distorted images that can be used for training. FIG. **2**E illustrates an example of the 2D image projection process **216**. As shown in FIG. **2**E, the electronic device **101** projects the ground truth image **202** twice, once using the left warp field **254** and once using the right warp field **254**. Each projection results in one of the training stereo pair **218***a*-**218***b*. The left training image **218***a* and the right training image **218***b* exhibit perspective distortion that is not present in the ground truth image **202**. The 2D image projection process **216** represents any suitable technique for 2D image projecting using a warp field.

Returning to FIG. **2**A, it is shown that the training data generation process **220** results in the training stereo pair **218***a*-**218***b*. The training stereo pair **218***a*-**218***b* can, in turn, be used as an input to the training process **240**, which is performed to generate a prediction image **238**. The training process **240** will now be described in greater detail.

In the training process **240**, the electronic device **101** obtains one or more pairs of distorted images **222***a*-**222***b*, which represent two distorted images (such as left and right distorted images) that exhibit perspective distortion in a person's face shown in the distorted images **222***a*-**222***b*. Each pair of distorted images **222***a*-**222***b* can represent a training stereo pair **218***a*-**218***b* generated during the training data generation process **220**. Using the distorted images **222***a*-**222***b* as input, the electronic device **101** performs a 2D baseline normalization process **224** to address variable parametric differences that can occur between different imaging sensors. For example, stereo imaging sensors used during training might be different than the imaging sensor used to generate a ground truth image **202**. Different imaging sensors and devices can exhibit parametric differences, such as sensor sensitivities, calibrations, focal lengths, and the baseline distance between the imaging sensors in a given device. The electronic device **101** performs the 2D baseline normalization process **224** to remove any baseline differences or "disparities" that exist between the distorted images **222***a*-**222***b*, thereby "normalizing" the distorted images **222***a*-**222***b*.

In some cases, the 2D baseline normalization process **224** removes the baseline disparity by aligning a subset of the landmark points **250** identified during the training data generation process **220** (such as only the nostrils of the face). Using the subset of landmark points **250**, the faces can be aligned between the distorted images **222***a*-**222***b* such that the landmark points **250** appear at nearby locations in the 2D grid. The 2D baseline normalization process **224** can use one or more transformations, such as an affine transformation, to align the images. An affine transformation can rotate an image (such as to account for sensor alignment), scale an image (such as to account for focal length differences), and translate an image (such as to account for baseline distance differences). This can be expressed mathematically as follows:

$$y=Ax+b \tag{5}$$

where y represents the coordinates of a transformed point, x represents the coordinates of an input point, A represents a matrix that models rotation and scaling, and b represents a vector that models translation.

FIG. **2**F illustrates an example of the 2D baseline normalization process **224**. As shown in FIG. **2**F, the electronic device **101** performs the 2D baseline normalization process **224** on an input image **256**, which can represent one of the distorted images **222***a*-**222***b*. The resulting image **258** exhibits one or more transformations, such as rotation, scaling, and translation. The resulting transformations depicted in the resulting images **256***a*-**256***b* are exaggerated as shown, but this illustrate the types of transformations that can occur.

The 2D baseline normalization process **224** can also account for brightness differences between sensors. For example, the 2D baseline normalization process **224** can use histogram equalization to make the images of the distorted images **222***a*-**222***b* have similar brightness. Of course, histogram equalization is only an example technique for equalizing brightness between images, and any other suitable technique can be used.

After the 2D baseline normalization process **224**, the electronic device **101** trains a disparity estimation network **226** using the distorted images **222***a*-**222***b*. The disparity estimation network **226** is a deep learning network (DNN), such as a convolutional neural network (CNN). Deep learning networks may require training using a large number (such as dozens, hundreds, or thousands) of training data to perform at high levels of accuracy. Thus, the electronic device **101** performs the training process **240**, in part, to train the disparity estimation network **226**. The disparity estimation network **226** accepts the distorted images **222***a*-**222***b* as input and, for each pair, predicts a depth map **244** (such as in units of pixels). Each depth map **244** is a mapping of how far an object is away from an imaging sensor as represented by each pixel. The disparity estimation network **226** represents any suitable deep learning network or other machine learning model that is trained to predict depth maps using distorted images. Each depth map **244** represents the depth of each pixel in the associated distorted images **222***a*-**222***b*. In some embodiments, the disparity estimation network **226** includes multiple layers, which can include one or more encoder layers, decoder layers, and the like.

After obtaining the depth map **244** using the disparity estimation network **226**, the electronic device **101** performs a depth calculation process **228** to convert the disparity from pixel units to physical distance units (such as meters, centimeters, inches, or the like) using one or more parameters of the imaging sensor model. Essentially, the depth calculation process **228** rescales the depth map **244** into different units to make the depth map **244** better suited for downstream processes.

After the electronic device **101** uses the disparity estimation network **226** to obtain a depth map **244**, the electronic device **101** performs a virtual imaging sensor transformation process **230** to "virtually" move a virtual imaging sensor further away from a subject. Moving the virtual imaging sensor to be further away corresponds to a reduction in perspective distortion as discussed above. In some embodiments, the virtual imaging sensor transformation process **230** includes adding a constant distance vector to every pixel in a selected one of the distorted images **222***a*-**222***b* (such as the distorted image **222***a*). After the virtual imaging sensor transformation process **230**, the electronic device **101** performs a warp field generation process **232** using the selected distorted image **222***a* to generate a warp field. The warp field generation process **232** is similar to the warp field generation process **214** of the training data generation process **220** discussed above, expect the warp field generated in the warp field generation process **232** is used to eliminate the distortion in the distorted image **222***a* (in contrast to the warp fields **254**, which are used to introduce distortion to the ground truth image **202**). Using the depth map **244** and the warp field generated in the warp field generation process **232**, the electronic device **101** performs a 2D image projection process **234** on the distorted image **222***a* to generate an undistorted image **260**, an example of which is shown in FIG. **2**G. The 2D image projection process **234** is similar to the 2D image projection process **216** of the training data generation process **220** discussed above.

As shown in FIG. **2**G, the undistorted image **260** generated using the 2D image projection process **216** may include one or more unfilled areas (or "holes") **262**, which represent missing pixels in the undistorted image **260**. The holes **262** can occur because the projection of a distorted image into an undistorted image may cause discrepancies that cannot be fully reconciled during the 2D image projection process **216**. For example, as the virtual imaging sensor is moved further away from the subject, additional areas surrounding the subject may be brought into view. To address this, the electronic device **101** implements an inpainting network **236** to "fill in" the holes **262** in the undistorted image **260**. FIG. **2**G illustrates an example use of the inpainting network **236**. As shown in FIG. **2**G, the inpainting network **236** receives the undistorted image **260** with holes **262** and generates a prediction image **238** without holes **262**. The inpainting network **236** represents any suitable learning network or other machine learning model that is trained to perform inpainting to fill holes in an image. In some embodiments, the inpainting network **236** is a deep learning network such as a CNN. In some embodiments, the electronic device **101** can perform the training process **240**, in part, to train the inpainting network **236**.

The prediction image **238** represents a prediction of what is actually shown in the ground truth image **202**. However, the prediction may not be entirely accurate, especially early in training. Thus, the training process **240** is performed iteratively, and a loss **242** can be calculated for each iteration. The loss **242** is calculated to represent the difference between the ground truth image **202** and the prediction image **238**. The electronic device **101** may calculate the loss **242** using any suitable metric for image quality, such as L1, structural similarity index (SSIM), multi-scale SSIM (MS-SSIM), and the like. An example of a loss function is given below:

$$\text{Loss}=\Sigma_{i=1}{}^{P}(X_i-\hat{X}_l)^2 \tag{6}$$

where X_i represents the value of the i^{th} pixel in the ground truth image **202**, and $\hat{X}_i$ represents the value of the i^{th} pixel in the prediction image **238**. Of course, this is merely one example, and other loss function calculations can be used. Once the loss **242** is calculated, the electronic device **101** uses the loss **242** to tune one or more network weights. For example, in the training process **240**, both the disparity estimation network **226** and the inpainting network **236** include weights that are updated based on the calculated loss **242**, such as via a backpropagation algorithm. Once the weights are updated, the electronic device **101** can perform another iteration of the training process **240**, and the iterations can continue until the loss **242** is acceptably small or until one or more other criteria are met (such as a specified amount of time elapsing or a specified number of training iterations completing).

Although FIGS. **2**A through **2**G illustrates one example of a training framework **200** for facial un-distortion in digital images using multiple imaging sensors and related details, various changes may be made to FIGS. **2**A through **2**G. For example, while the framework **200** is described with various examples of machine learning models and tasks, other embodiments could include other machine learning models and/or other tasks. Also, while shown as a specific sequence of operations, various operations shown in FIGS. **2**A through **2**G could overlap, occur in parallel, occur in a different order, or occur any number of times (including zero times). In addition, the specific operations shown in FIGS. **2**A through **2**G are examples only, and other techniques could be used to perform each of the operations shown in FIGS. **2**A through **2**G.

FIG. **3** illustrates an example process **300** for facial un-distortion in digital images using multiple imaging sensors according to this disclosure. For ease of explanation, the process **300** is described as being implemented using one or more components of the electronic device **101**, which in this case can represent a consumer electronic device (such as a smartphone). However, this is merely one example, and the process **300** could be implemented using any other suitable device(s), such as when implemented using the server **106**.

As shown in FIG. **3**, the process **300** uses many of the same components and operations as the training process **240** of the framework **200**. In this example, the electronic device **101** obtains two images **302***a*-**302***b* of a scene that show a face of a person in the scene. For example, the electronic device **101** may include dual imaging sensors **180**, and the images **302***a*-**302***b* may be captured by the dual imaging sensors **180** of the electronic device **101** at the same time. Each of the images **302***a*-**302***b* may a selfie captured by a user of the electronic device **101** and may include an amount of perspective distortion, including around the user's face.

Using the images **302***a*-**302***b* as input, the electronic device **101** performs the 2D baseline normalization process **224** to address parametric differences that can occur between the dual imaging sensors of the electronic device **101**. For example, the electronic device **101** may perform the 2D baseline normalization process **224** to remove any baseline disparities that exist between the images **302***a*-**302***b*, thereby aligning the images **302***a*-**302***b*. After the 2D baseline normalization process **224**, the electronic device **101** provides the aligned images **302***a*-**302***b* as input to the disparity estimation network **226**. The disparity estimation network uses the aligned images **302***a*-**302***b* to predict the depth map **244**, such as in units of pixels. The electronic device **101** also performs a depth calculation process **228** to convert the disparity from pixel units to physical distance units (such as meters, centimeters, inches, or the like).

The electronic device **101** performs the virtual imaging sensor transformation process **230** to "virtually" make the subject in the images **302***a*-**302***b* appear more distant. After the virtual imaging sensor transformation process **230**, the electronic device **101** performs a warp field generation process **232** to generate a warp field, which is used to eliminate the distortion in a selected one of the images **302***a*-**302***b* (such as the image **302***a*). Using the warp field generated in the warp field generation process **232**, the electronic device **101** performs a 2D image projection process **234** on the image **302***a* to generate an undistorted image **260**. The electronic device **101** implements the inpainting network **236** to fill in any holes **262** (such as missing pixels) in the undistorted image **260** and generate a final undistorted image **304**. The final undistorted image **304** can be output, saved, displayed to a user of the electronic device **101**, provided as input to another image processing technique, or used in any other suitable manner.

Although FIG. **3** illustrates one example of a process **300** for facial un-distortion in digital images using multiple imaging sensors, various changes may be made to FIG. **3**. For example, while the images **302***a*-**302***b* are described as being captured by imaging sensors **180** of the electronic device **101**, the images **302***a*-**302***b* could be captured by dual imaging sensors of another device and later sent to the electronic device **101**. Also, while shown as a specific sequence of operations, various operations shown in FIG. **3** could overlap, occur in parallel, occur in a different order, or occur any number of times (including zero times). In addition, the specific operations shown in FIG. **3** are examples only, and other techniques could be used to perform each of the operations shown in FIG. **3**.

Note that the operations and functions shown in FIGS. **2**A through **3** can be implemented in an electronic device **101**, server **106**, or other device in any suitable manner. For example, in some embodiments, the operations and functions shown in FIGS. **2**A through **3** can be implemented or supported using one or more software applications or other software instructions that are executed by the processor **120** of the electronic device **101**, server **106**, or other device. In other embodiments, at least some of the operations and functions shown in FIGS. **2**A through **3** can be implemented or supported using dedicated hardware components. In general, the operations and functions shown in FIGS. **2**A through **3** can be performed using any suitable hardware or any suitable combination of hardware and software/firmware instructions.

FIGS. **4**A through **4**C illustrate examples of benefits that can be realized using one or more of the embodiments of this disclosure. In FIGS. **4**A and **4**B, the images **401** and **402** were captured at the same time by two imaging sensors of a dual imaging sensor smartphone. As evident by FIGS. **4**A and **4**B, the images **401** and **402** exhibit perspective distortion. For example, the subject's face is too narrow, while the subject's nose and mouth are exaggerated. In FIG. **4**C, the image **403** is obtained by performing the facial un-distortion process **300** using the disparity estimation network **226** and inpainting network **236**, which have been trained using the training process **240**. As evident by FIG. **4**C, the resulting image **403** shows the subject's face without distortion; for example, the mouth and nose appear distortion free in FIG. **4**C. It is noted that the subject's eyes have been hidden in the images **401**-**403** for privacy reasons.

Although FIGS. **4**A through **4**C illustrate examples of benefits that can be realized using one or more of the embodiments of this disclosure, various changes may be made to FIGS. **4**A through **4**C. For example, images can be captured of numerous scenes under different lighting conditions and from different distances and angles, and these figures do not limit the scope of this disclosure. These figures are merely meant to illustrate example types of benefits that might be obtainable using the techniques described above.

FIG. **5** illustrates an example method **500** for facial un-distortion in digital images using multiple imaging sensors according to this disclosure. For ease of explanation, the method **500** shown in FIG. **5** is described as involving the use of the electronic device **101** shown in FIG. **1** and the process **300** shown in FIG. **3**. However, the method **500** shown in FIG. **5** could be used with any other suitable electronic device (such as the server **106**) and any suitable process.

As shown in FIG. **5**, landmark points are aligned between multiple distorted images to generate multiple aligned images at step **502**. This could include, for example, the electronic device **101** aligning landmark points **250** between the distorted images **222***a*-**222***b* to generate multiple aligned images **222***a*-**222***b*. The multiple distorted images exhibit perspective distortion in at least one face appearing in the multiple distorted images. A depth map is predicted using a disparity estimation neural network that receives the multiple aligned images as input at step **504**. This could include, for example, the electronic device **101** predicting the depth map **244** using the disparity estimation network **226**, which receives the multiple aligned images **222***a*-**222***b* as input.

A warp field is generated using a selected one of the multiple aligned images at step **506**. This could include, for example, the electronic device **101** performing the warp field generation process **232** using a selected one of the multiple aligned images **222***a*-**222***b* to generate a warp field **254**. A 2D image projection is performed on the selected aligned image using the depth map and the warp field to generate an undistorted image at step **508**. This could include, for example, the electronic device **101** performing the 2D image projection process **234** to generate an undistorted image **260**. One or more missing pixels are filled in within the undistorted image using an inpainting neural network to generate a final undistorted image at step **510**. This could include, for example, the electronic device **101** implementing the inpainting network **236** to fill in one or more missing pixels in the undistorted image **260** to generate the final undistorted image **304**.

Although FIG. **5** illustrates one example of a method **500** for facial un-distortion in digital images using multiple imaging sensors, various changes may be made to FIG. **5**. For example, while shown as a series of steps, various steps in FIG. **5** could overlap, occur in parallel, occur in a different order, or occur any number of times.

FIG. **6** illustrates an example method **600** for generating and using training data according to this disclosure. For ease of explanation, the method **600** shown in FIG. **6** is described as involving the use of the electronic device **101** shown in FIG. **1** and the framework **200** shown in FIGS. **2**A through **2**G. However, the method **600** shown in FIG. **6** could be used with any other suitable electronic device (such as the server **106**) and any suitable process.

As shown in FIG. **6**, landmark points are identified on a face portion of a person appearing in an undistorted ground truth image at step **602**. This could include, for example, the electronic device **101** identifying landmark points **250** on a face portion of a person appearing in the ground truth image **202**. A 3D face model is generated that fits the landmark points of the face portion at step **604**. This could include, for example, the electronic device **101** generating the 3D model **252**, which fits the landmark points **250** of the face portion. The 3D face model includes depth information of the face portion.

A strong perspective projection is performed using the undistorted ground truth image and the depth information of the face portion to generate left and right distorted image pixel locations at step **606**. This could include, for example, the electronic device **101** performing the weak-to-strong perspective transformation process **208** using the ground truth image **202** and the depth information of the face portion to generate left and right distorted image pixel locations (x', y'). Left and right warp fields are generated based on the left and right distorted image pixel locations at step **608**. This could include, for example, the electronic device **101** generating the left and right warp fields **254** based on the left and right distorted image pixel locations. A 2D image projection is performed on the undistorted ground truth image using the 3D face model and the left and right warp fields to generate a stereo image pair at step **610**. This could include, for example, the electronic device **101** performing the 2D image projection process **216** on the ground truth image **202** using the 3D model **252** and the left and right warp fields **254** to generate the training stereo pair **218***a*-**218***b*.

Although FIG. **6** illustrates one example of a method **600** for generating and using training data, various changes may be made to FIG. **6**. For example, while shown as a series of steps, various steps in FIG. **6** could overlap, occur in parallel, occur in a different order, or occur any number of times.

Although this disclosure has been described with reference to various example embodiments, various changes and modifications may be suggested to one skilled in the art. It is intended that this disclosure encompass such changes and modifications as fall within the scope of the appended claims.

What is claimed is:

1. A method comprising:

aligning landmark points between multiple distorted images to generate multiple aligned images, wherein the multiple distorted images exhibit perspective distortion in at least one face appearing in the multiple distorted images, and wherein the landmark points are aligned to correct baseline disparities between the multiple distorted images caused by differences in at least one of: sensor sensitivities, calibrations, focal lengths, and baseline distance between imaging sensors;

predicting a depth map using a disparity estimation neural network that receives the multiple aligned images as input;

generating a warp field using a selected one of the multiple aligned images;

performing a two-dimensional (2D) image projection on the selected aligned image using the depth map and the warp field to generate an undistorted image, wherein the undistorted image includes one or more missing pixels as a result of the 2D image projection; and

filling in the one or more missing pixels in the undistorted image using an inpainting neural network to generate a final undistorted image.

2. The method of claim **1**, wherein the disparity estimation neural network and the inpainting neural network are trained by adjusting weights based on a loss value determined according to differences between an undistorted ground truth image and a predicted image generated using the disparity estimation neural network and the inpainting neural network.

3. The method of claim **1**, wherein the multiple distorted images are captured by dual imaging sensors of an electronic device.

4. The method of claim **1**, further comprising:

before generating the warp field, virtually making one or more subjects in the selected aligned image more distant by adding a constant distance vector to each pixel in the selected aligned image.

5. The method of claim **1**, wherein the landmark points are aligned using an affine transformation.

6. A method comprising:

aligning landmark points between multiple distorted images to generate multiple aligned images, wherein the multiple distorted images exhibit perspective distortion in at least one face appearing in the multiple distorted images;

adjusting for brightness differences between the multiple distorted images using histogram equalization such that the multiple distorted images have similar brightness;

predicting a depth map using a disparity estimation neural network that receives the multiple aligned images as input;

generating a warp field using a selected one of the multiple aligned images;

performing a two-dimensional (2D) image projection on the selected aligned image using the depth map and the warp field to generate an undistorted image, wherein the undistorted image includes one or more missing pixels as a result of the 2D image projection;

filling in the one or more missing pixels in the undistorted image using an inpainting neural network to generate a final undistorted image.

7. An electronic device comprising:

at least one memory configured to store instructions; and

at least one processing device configured when executing the instructions to:

align landmark points between multiple distorted images to generate multiple aligned images, wherein the multiple distorted images exhibit perspective distortion in at least one face appearing in the multiple distorted images;

predict a depth map using a disparity estimation neural network that receives the multiple aligned images as input;

generate a warp field using a selected one of the multiple aligned images;

perform a two-dimensional (2D) image projection on the selected aligned image using the depth map and the warp field to generate an undistorted image, wherein the undistorted image includes one or more missing pixels as a result of the 2D image projection; and

fill in the one or more missing pixels in the undistorted image using an inpainting neural network to generate a final undistorted image;

wherein the disparity estimation neural network and the inpainting neural network are trained by adjusting weights based on a loss value determined according to differences between an undistorted ground truth image and a predicted image generated using the disparity estimation neural network and the inpainting neural network.

8. The electronic device of claim **7**, wherein the multiple distorted images comprise images captured by dual imaging sensors of the electronic device or another electronic device.

9. The electronic device of claim **7**, wherein the at least one processing device is further configured when executing the instructions to:

before generating the warp field, virtually make one or more subjects in the selected aligned image more distant by adding a constant distance vector to each pixel in the selected aligned image.

10. The electronic device of claim **7**, wherein the at least one processing device is configured to align the landmark points to correct baseline disparities between the multiple distorted images caused by differences in at least one of: sensor sensitivities, calibrations, focal lengths, and baseline distance between imaging sensors.

11. The electronic device of claim **7**, wherein the at least one processing device is configured to align the landmark points using an affine transformation.

12. The electronic device of claim **7**, wherein the at least one processing device is further configured when executing the instructions to adjust for brightness differences between the multiple distorted images using histogram equalization such that the multiple distorted images have similar brightness.

13. A non-transitory machine-readable medium containing instructions that when executed cause at least one processor of an electronic device to:

align landmark points between multiple distorted images to generate multiple aligned images, wherein the multiple distorted images exhibit perspective distortion in at least one face appearing in the multiple distorted images;

predict a depth map using a disparity estimation neural network that receives the multiple aligned images as input;

virtually make one or more subjects in a selected one of the multiple aligned images more distant by adding a constant distance vector to each pixel in the selected aligned image;

generate a warp field using the selected aligned image;

perform a two-dimensional (2D) image projection on the selected aligned image using the depth map and the warp field to generate an undistorted image, wherein the undistorted image includes one or more missing pixels as a result of the 2D image projection; and

fill in the one or more missing pixels in the undistorted image using an inpainting neural network to generate a final undistorted image.

14. The non-transitory machine-readable medium of claim **13**, wherein the disparity estimation neural network and the inpainting neural network are trained by adjusting weights based on a loss value determined according to differences between an undistorted ground truth image and a predicted image generated using the disparity estimation neural network and the inpainting neural network.

15. The non-transitory machine-readable medium of claim **13**, wherein the multiple distorted images comprise images captured by dual imaging sensors of the electronic device or another electronic device.

16. The non-transitory machine-readable medium of claim **13**, wherein the instructions when executed cause at least one processor to align the landmark points to correct baseline disparities between the multiple distorted images caused by differences in at least one of: sensor sensitivities, calibrations, focal lengths, and baseline distance between imaging sensors.

17. The non-transitory machine-readable medium of claim **13**, wherein the instructions when executed cause the at least one processor to align the landmark points using an affine transformation.

18. The method of claim **6**, wherein the landmark points are aligned to correct baseline disparities between the multiple distorted images caused by differences in at least one of: sensor sensitivities, calibrations, focal lengths, and baseline distance between imaging sensors.

19. The method of claim **6**, further comprising:

before generating the warp field, virtually making one or more subjects in the selected aligned image more distant by adding a constant distance vector to each pixel in the selected aligned image.

20. The method of claim **18**, further comprising:

before generating the warp field, virtually making one or more subjects in the selected aligned image more distant by adding a constant distance vector to each pixel in the selected aligned image.

21. The method of claim **6**, wherein the disparity estimation neural network and the inpainting neural network are trained by adjusting weights based on a loss value determined according to differences between an undistorted ground truth image and a predicted image generated using the disparity estimation neural network and the inpainting neural network.

22. The method of claim **18**, wherein the disparity estimation neural network and the inpainting neural network are trained by adjusting weights based on a loss value determined according to differences between an undistorted ground truth image and a predicted image generated using the disparity estimation neural network and the inpainting neural network.

23. The method of claim **19**, wherein the disparity estimation neural network and the inpainting neural network are trained by adjusting weights based on a loss value determined according to differences between an undistorted ground truth image and a predicted image generated using the disparity estimation neural network and the inpainting neural network.

24. The method of claim **20**, wherein the disparity estimation neural network and the inpainting neural network are trained by adjusting weights based on a loss value determined according to differences between an undistorted ground truth image and a predicted image generated using the disparity estimation neural network and the inpainting neural network.

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