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**Guler et al.**

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(54) **BODY MESH RECONSTRUCTION FROM RGB IMAGE**

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(58) **Field of Classification Search**
None
See application file for complete search history.

(56) **References Cited**

U.S. PATENT DOCUMENTS

| | | | |
|---|---|---|---|
| 5,604,843 | A | 2/1997 | Shaw et al. |
| 5,689,559 | A | 11/1997 | Park |

(Continued)

FOREIGN PATENT DOCUMENTS

| | | | |
|---|---|---|---|
| CN | 109863532 | A | 6/2019 |
| CN | 110168478 | A | 8/2019 |

(Continued)

OTHER PUBLICATIONS

"U.S. Appl. No. 18/134,347, Non Final Office Action mailed Mar. 6, 2025", 16 pgs.

(Continued)

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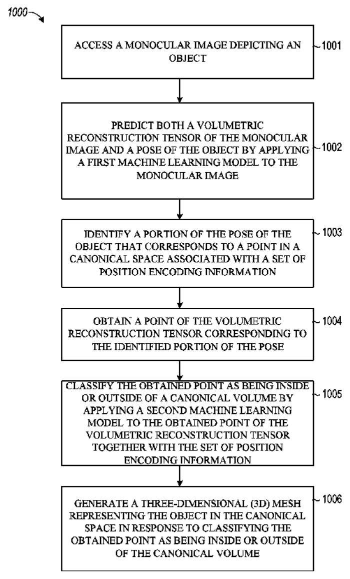
(57) **ABSTRACT**

Methods and systems are disclosed for generating a body mesh from a single image. The system predicts both a volumetric reconstruction tensor of the monocular image and a pose of an object by applying a first machine learning model to a monocular image. The system identifies a portion of the pose of the object that corresponds to a point in a canonical space associated with a set of position encoding information. The system obtains a point of the volumetric reconstruction tensor corresponding to the identified portion of the pose. The system classifies the obtained point as being inside or outside of a canonical volume by applying a second machine learning model to the obtained point of the volumetric reconstruction tensor together with the set of position encoding information. The system generates a three-dimensional (3D) mesh representing the object in the canonical space.

**20 Claims, 13 Drawing Sheets**


1000
ACCESS A MONOCULAR IMAGE DEPICTING AN OBJECT
1001
PREDICT BOTH A VOLUMETRIC RECONSTRUCTION TENSOR OF THE MONOCULAR IMAGE AND A POSE OF THE OBJECT BY APPLYING A FIRST MACHINE LEARNING MODEL TO THE MONOCULAR IMAGE
1002
IDENTIFY A PORTION OF THE POSE OF THE OBJECT THAT CORRESPONDS TO A POINT IN A CANONICAL SPACE ASSOCIATED WITH A SET OF POSITION ENCODING INFORMATION
1003
OBTAIN A POINT OF THE VOLUMETRIC RECONSTRUCTION TENSOR CORRESPONDING TO THE IDENTIFIED PORTION OF THE POSE
1004
CLASSIFY THE OBTAINED POINT AS BEING INSIDE OR OUTSIDE OF A CANONICAL VOLUME BY APPLYING A SECOND MACHINE LEARNING MODEL TO THE OBTAINED POINT OF THE VOLUMETRIC RECONSTRUCTION TENSOR TOGETHER WITH THE SET OF POSITION ENCODING INFORMATION
1005
GENERATE A THREE-DIMENSIONAL (3D) MESH REPRESENTING THE OBJECT IN THE CANONICAL SPACE IN RESPONSE TO CLASSIFYING THE OBTAINED POINT AS BEING INSIDE OR OUTSIDE OF THE CANONICAL VOLUME
1006

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(56) **References Cited**

U.S. PATENT DOCUMENTS

| | | | |
|---|---|---|---|
| 5,880,731 | A | 3/1999 | Liles et al. |
| 6,023,270 | A | 2/2000 | Brush, II et al. |
| RE36,919 | E | 10/2000 | Park |
| RE37,052 | E | 2/2001 | Park |
| 6,223,165 | B1 | 4/2001 | Lauffer |
| 6,650,793 | B1 | 11/2003 | Lund et al. |
| 6,772,195 | B1 | 8/2004 | Hatlelid et al. |
| 6,804,417 | B1 | 10/2004 | Lund et al. |
| 6,842,779 | B1 | 1/2005 | Nishizawa |
| 7,342,587 | B2 | 3/2008 | Danzig et al. |
| 7,468,729 | B1 | 12/2008 | Levinson |
| 7,636,755 | B2 | 12/2009 | Blattner et al. |
| 7,639,251 | B2 | 12/2009 | Gu et al. |
| 7,775,885 | B2 | 8/2010 | Van et al. |
| 7,859,551 | B2 | 12/2010 | Bulman et al. |
| 7,885,931 | B2 | 2/2011 | Seo et al. |
| 7,925,703 | B2 | 4/2011 | Dinan et al. |
| 8,088,044 | B2 | 1/2012 | Tchao et al. |
| 8,095,878 | B2 | 1/2012 | Bates et al. |
| 8,108,774 | B2 | 1/2012 | Finn et al. |
| 8,117,281 | B2 | 2/2012 | Robinson et al. |
| 8,130,219 | B2 | 3/2012 | Fleury et al. |
| 8,146,005 | B2 | 3/2012 | Jones et al. |
| 8,151,191 | B2 | 4/2012 | Nicol |
| RE43,993 | E | 2/2013 | Park |
| 8,384,719 | B2 | 2/2013 | Reville et al. |
| RE44,054 | E | 3/2013 | Kim |
| RE44,068 | E | 3/2013 | Park |
| RE44,106 | E | 3/2013 | Park |
| 8,396,708 | B2 | 3/2013 | Park et al. |
| RE44,121 | E | 4/2013 | Park |
| 8,425,322 | B2 | 4/2013 | Gillo et al. |
| 8,458,601 | B2 | 6/2013 | Castelli et al. |
| 8,462,198 | B2 | 6/2013 | Lin et al. |
| 8,484,158 | B2 | 7/2013 | Deluca et al. |
| 8,495,503 | B2 | 7/2013 | Brown et al. |
| 8,495,505 | B2 | 7/2013 | Smith et al. |
| 8,504,926 | B2 | 8/2013 | Wolf |
| 8,559,980 | B2 | 10/2013 | Pujol |
| 8,564,621 | B2 | 10/2013 | Branson et al. |
| 8,564,710 | B2 | 10/2013 | Nonaka et al. |
| 8,581,911 | B2 | 11/2013 | Becker et al. |
| 8,597,121 | B2 | 12/2013 | del Valle |
| 8,601,051 | B2 | 12/2013 | Wang |
| 8,601,379 | B2 | 12/2013 | Marks et al. |
| 8,632,408 | B2 | 1/2014 | Gillo et al. |
| 8,648,865 | B2 | 2/2014 | Dawson et al. |
| 8,659,548 | B2 | 2/2014 | Hildreth |
| 8,683,354 | B2 | 3/2014 | Khandelwal et al. |
| 8,692,830 | B2 | 4/2014 | Nelson et al. |
| 8,810,513 | B2 | 8/2014 | Ptucha et al. |
| 8,812,171 | B2 | 8/2014 | Filev et al. |
| 8,832,201 | B2 | 9/2014 | Wall |
| 8,832,552 | B2 | 9/2014 | Arrasvuori et al. |
| 8,839,327 | B2 | 9/2014 | Amento et al. |
| 8,890,926 | B2 | 11/2014 | Tandon et al. |
| 8,892,999 | B2 | 11/2014 | Nims et al. |
| 8,924,250 | B2 | 12/2014 | Bates et al. |
| 8,963,926 | B2 | 2/2015 | Brown et al. |
| 8,989,786 | B2 | 3/2015 | Feghali |
| 9,086,776 | B2 | 7/2015 | Ye et al. |
| 9,105,014 | B2 | 8/2015 | Collet et al. |
| 9,241,184 | B2 | 1/2016 | Weerasinghe |
| 9,256,860 | B2 | 2/2016 | Herger et al. |
| 9,298,257 | B2 | 3/2016 | Hwang et al. |
| 9,314,692 | B2 | 4/2016 | Konoplev et al. |
| 9,330,483 | B2 | 5/2016 | Du et al. |
| 9,357,174 | B2 | 5/2016 | Li et al. |
| 9,361,510 | B2 | 6/2016 | Yao et al. |
| 9,378,576 | B2 | 6/2016 | Bouaziz et al. |
| 9,402,057 | B2 | 7/2016 | Kaytaz et al. |
| 9,412,192 | B2 | 8/2016 | Mandel et al. |
| 9,460,541 | B2 | 10/2016 | Li et al. |
| 9,489,760 | B2 | 11/2016 | Li et al. |
| 9,503,845 | B2 | 11/2016 | Vincent |
| 9,508,197 | B2 | 11/2016 | Quinn et al. |
| 9,532,364 | B2 | 12/2016 | Fujito |
| 9,544,257 | B2 | 1/2017 | Ogundokun et al. |
| 9,576,400 | B2 | 2/2017 | Van Os et al. |
| 9,589,357 | B2 | 3/2017 | Li et al. |
| 9,592,449 | B2 | 3/2017 | Barbalet et al. |
| 9,648,376 | B2 | 5/2017 | Chang et al. |
| 9,697,635 | B2 | 7/2017 | Quinn et al. |
| 9,706,040 | B2 | 7/2017 | Kadirvel et al. |
| 9,744,466 | B2 | 8/2017 | Fujioka |
| 9,746,990 | B2 | 8/2017 | Anderson et al. |
| 9,749,270 | B2 | 8/2017 | Collet et al. |
| 9,792,714 | B2 | 10/2017 | Li et al. |
| 9,839,844 | B2 | 12/2017 | Dunstan et al. |
| 9,883,838 | B2 | 2/2018 | Kaleal, III et al. |
| 9,898,849 | B2 | 2/2018 | Du et al. |
| 9,911,073 | B1 | 3/2018 | Spiegel et al. |
| 9,936,165 | B2 | 4/2018 | Li et al. |
| 9,959,037 | B2 | 5/2018 | Chaudhri et al. |
| 9,980,100 | B1 | 5/2018 | Charlton et al. |
| 9,990,373 | B2 | 6/2018 | Fortkort |
| 10,039,988 | B2 | 8/2018 | Lobb et al. |
| 10,097,492 | B2 | 10/2018 | Tsuda et al. |
| 10,116,598 | B2 | 10/2018 | Tucker et al. |
| 10,155,168 | B2 | 12/2018 | Blackstock et al. |
| 10,158,589 | B2 | 12/2018 | Collet et al. |
| 10,242,477 | B1 | 3/2019 | Charlton et al. |
| 10,242,503 | B2 | 3/2019 | McPhee et al. |
| 10,262,250 | B1 | 4/2019 | Spiegel et al. |
| 10,348,662 | B2 | 7/2019 | Baldwin et al. |
| 10,362,219 | B2 | 7/2019 | Wilson et al. |
| 10,432,559 | B2 | 10/2019 | Baldwin et al. |
| 10,454,857 | B1 | 10/2019 | Blackstock et al. |
| 10,475,225 | B2 | 11/2019 | Park et al. |
| 10,504,266 | B2 | 12/2019 | Blattner et al. |
| 10,573,048 | B2 | 2/2020 | Ni et al. |
| 10,656,797 | B1 | 5/2020 | Alvi et al. |
| 10,657,695 | B2 | 5/2020 | Chand et al. |
| 10,657,701 | B2 | 5/2020 | Osman et al. |
| 10,762,174 | B2 | 9/2020 | Denton et al. |
| 10,805,248 | B2 | 10/2020 | Luo et al. |
| 10,872,451 | B2 | 12/2020 | Sheth et al. |
| 10,880,246 | B2 | 12/2020 | Baldwin et al. |
| 10,895,964 | B1 | 1/2021 | Grantham et al. |
| 10,896,534 | B1 | 1/2021 | Smith et al. |
| 10,933,311 | B2 | 3/2021 | Brody et al. |
| 10,938,758 | B2 | 3/2021 | Allen et al. |
| 10,964,082 | B2 | 3/2021 | Amitay et al. |
| 10,979,752 | B1 | 4/2021 | Brody et al. |
| 10,984,575 | B2 | 4/2021 | Assouline et al. |
| 10,992,619 | B2 | 4/2021 | Antmen et al. |
| 11,010,022 | B2 | 5/2021 | Alvi et al. |
| 11,030,789 | B2 | 6/2021 | Chand et al. |
| 11,036,781 | B1 | 6/2021 | Baril et al. |
| 11,063,891 | B2 | 7/2021 | Voss |
| 11,069,103 | B1 | 7/2021 | Blackstock et al. |
| 11,080,917 | B2 | 8/2021 | Monroy-hernÁNdez et al. |
| 11,128,586 | B2 | 9/2021 | Al Majid et al. |
| 11,188,190 | B2 | 11/2021 | Blackstock et al. |
| 11,189,070 | B2 | 11/2021 | Jahangiri et al. |
| 11,199,957 | B1 | 12/2021 | Alvi et al. |
| 11,218,433 | B2 | 1/2022 | Baldwin et al. |
| 11,229,849 | B2 | 1/2022 | Blackstock et al. |
| 11,245,658 | B2 | 2/2022 | Grantham et al. |
| 11,249,614 | B2 | 2/2022 | Brody |
| 11,263,254 | B2 | 3/2022 | Baril et al. |
| 11,270,491 | B2 | 3/2022 | Monroy-HernÁNdez et al. |
| 11,284,144 | B2 | 3/2022 | Kotsopoulos et al. |
| 11,361,507 | B1 * | 6/2022 | Iqbal ....................... G06T 19/20 |
| 11,893,675 | B1 | 2/2024 | Bhushan et al. |

(56) **References Cited**

U.S. PATENT DOCUMENTS

| | | | |
|---|---|---|---|
| 12,136,180 | B1 | 11/2024 | Karumuri et al. |
| 2002/0067362 | A1 | 6/2002 | Agostino Nocera et al. |
| 2002/0169644 | A1 | 11/2002 | Greene |
| 2005/0162419 | A1 | 7/2005 | Kim et al. |
| 2005/0206610 | A1 | 9/2005 | Cordelli |
| 2006/0294465 | A1 | 12/2006 | Ronen et al. |
| 2007/0113181 | A1 | 5/2007 | Blattner et al. |
| 2007/0168863 | A1 | 7/2007 | Blattner et al. |
| 2007/0176921 | A1 | 8/2007 | Iwasaki et al. |
| 2008/0158222 | A1 | 7/2008 | Li et al. |
| 2009/0016617 | A1 | 1/2009 | Bregman-Amitai et al. |
| 2009/0055484 | A1 | 2/2009 | Vuong et al. |
| 2009/0070688 | A1 | 3/2009 | Gyorfi et al. |
| 2009/0099925 | A1 | 4/2009 | Mehta et al. |
| 2009/0106672 | A1 | 4/2009 | Burstrom |
| 2009/0158170 | A1 | 6/2009 | Narayanan et al. |
| 2009/0177976 | A1 | 7/2009 | Bokor et al. |
| 2009/0202114 | A1 | 8/2009 | Morin et al. |
| 2009/0265604 | A1 | 10/2009 | Howard et al. |
| 2009/0300525 | A1 | 12/2009 | Jolliff et al. |
| 2009/0303984 | A1 | 12/2009 | Clark et al. |
| 2010/0011422 | A1 | 1/2010 | Mason et al. |
| 2010/0023885 | A1 | 1/2010 | Reville et al. |
| 2010/0115426 | A1 | 5/2010 | Liu et al. |
| 2010/0162149 | A1 | 6/2010 | Sheleheda et al. |
| 2010/0203968 | A1 | 8/2010 | Gill et al. |
| 2010/0227682 | A1 | 9/2010 | Reville et al. |
| 2011/0093780 | A1 | 4/2011 | Dunn |
| 2011/0115798 | A1 | 5/2011 | Nayar et al. |
| 2011/0148864 | A1 | 6/2011 | Lee et al. |
| 2011/0239136 | A1 | 9/2011 | Goldman et al. |
| 2012/0113106 | A1 | 5/2012 | Choi et al. |
| 2012/0124458 | A1 | 5/2012 | Cruzada |
| 2012/0130717 | A1 | 5/2012 | Xu et al. |
| 2013/0103760 | A1 | 4/2013 | Golding et al. |
| 2013/0201187 | A1 | 8/2013 | Tong et al. |
| 2013/0249948 | A1 | 9/2013 | Reitan |
| 2013/0257877 | A1 | 10/2013 | Davis |
| 2014/0043329 | A1 | 2/2014 | Wang et al. |
| 2014/0055554 | A1 | 2/2014 | Du et al. |
| 2014/0125678 | A1 | 5/2014 | Wang et al. |
| 2014/0129343 | A1 | 5/2014 | Finster et al. |
| 2015/0206349 | A1 | 7/2015 | Rosenthal et al. |
| 2016/0134840 | A1 | 5/2016 | Mcculloch |
| 2016/0234149 | A1 | 8/2016 | Tsuda et al. |
| 2017/0080346 | A1 | 3/2017 | Abbas |
| 2017/0087473 | A1 | 3/2017 | Siegel et al. |
| 2017/0113140 | A1 | 4/2017 | Blackstock et al. |
| 2017/0118145 | A1 | 4/2017 | Aittoniemi et al. |
| 2017/0199855 | A1 | 7/2017 | Fishbeck |
| 2017/0235848 | A1 | 8/2017 | Van Dusen et al. |
| 2017/0310934 | A1 | 10/2017 | Du et al. |
| 2017/0312634 | A1 | 11/2017 | Ledoux et al. |
| 2018/0047200 | A1 | 2/2018 | O'hara et al. |
| 2018/0113587 | A1 | 4/2018 | Allen et al. |
| 2018/0115503 | A1 | 4/2018 | Baldwin et al. |
| 2018/0197331 | A1 | 7/2018 | Chen et al. |
| 2018/0198743 | A1 | 7/2018 | Blackstock et al. |
| 2018/0315076 | A1 | 11/2018 | Andreou |
| 2018/0315133 | A1 | 11/2018 | Brody et al. |
| 2018/0315134 | A1 | 11/2018 | Amitay et al. |
| 2019/0001223 | A1 | 1/2019 | Blackstock et al. |
| 2019/0057616 | A1 | 2/2019 | Cohen et al. |
| 2019/0097958 | A1 | 3/2019 | Collet et al. |
| 2019/0188920 | A1 | 6/2019 | Mcphee et al. |
| 2019/0280997 | A1 | 9/2019 | Baldwin et al. |
| 2020/0306637 | A1 | 10/2020 | Baldwin et al. |
| 2020/0372127 | A1 | 11/2020 | Denton et al. |
| 2020/0410575 | A1 | 12/2020 | Grantham et al. |
| 2021/0074047 | A1 | 3/2021 | Sheth et al. |
| 2021/0089179 | A1 | 3/2021 | Grantham et al. |
| 2021/0104087 | A1 | 4/2021 | Smith et al. |
| 2021/0168108 | A1 | 6/2021 | Antmen et al. |
| 2021/0170270 | A1 | 6/2021 | Brody et al. |
| 2021/0192823 | A1 | 6/2021 | Amitay et al. |
| 2021/0209825 | A1 | 7/2021 | Assouline et al. |
| 2021/0225058 | A1 | 7/2021 | Chand et al. |
| 2021/0240315 | A1 | 8/2021 | Alvi et al. |
| 2021/0243482 | A1 | 8/2021 | Baril et al. |
| 2021/0243503 | A1 | 8/2021 | Kotsopoulos et al. |
| 2021/0266277 | A1 | 8/2021 | Allen et al. |
| 2021/0281897 | A1 | 9/2021 | Brody et al. |
| 2021/0285774 | A1 | 9/2021 | Collins et al. |
| 2021/0306290 | A1 | 9/2021 | Voss |
| 2021/0306451 | A1 | 9/2021 | Heikkinen et al. |
| 2021/0385180 | A1 | 12/2021 | Al Majid et al. |
| 2021/0405831 | A1 | 12/2021 | Mourkogiannis et al. |
| 2021/0409535 | A1 | 12/2021 | Mourkogiannis et al. |
| 2022/0012929 | A1 | 1/2022 | Blackstock et al. |
| 2022/0063605 | A1* | 3/2022 | Ji ........................ G06F 18/2193 |
| 2022/0335647 | A1* | 10/2022 | Shrivastava ........... G06V 10/82 |
| 2023/0088866 | A1 | 3/2023 | Stuyck et al. |
| 2023/0245192 | A1* | 8/2023 | Zaki ................... G06Q 30/0643 705/26.5 |
| 2024/0029358 | A1 | 1/2024 | Sharma et al. |
| 2024/0242435 | A1 | 7/2024 | Wang et al. |
| 2024/0346762 | A1 | 10/2024 | Dudovitch et al. |

FOREIGN PATENT DOCUMENTS

| | | | |
|---|---|---|---|
| EP | 2184092 | A2 | 5/2010 |
| JP | 2001230801 | A | 8/2001 |
| JP | 5497931 | B2 | 3/2014 |
| KR | 101445263 | B1 | 9/2014 |
| WO | WO-2003094072 | A1 | 11/2003 |
| WO | WO-2004095308 | A1 | 11/2004 |
| WO | WO-2006107182 | A1 | 10/2006 |
| WO | WO-2007134402 | A1 | 11/2007 |
| WO | WO-2012139276 | A1 | 10/2012 |
| WO | WO-2013027893 | A1 | 2/2013 |
| WO | WO-2013152454 | A1 | 10/2013 |
| WO | WO-2013166588 | A1 | 11/2013 |
| WO | WO-2014031899 | A1 | 2/2014 |
| WO | WO-2014194439 | A1 | 12/2014 |
| WO | WO-2016090605 | A1 | 6/2016 |
| WO | WO-2018081013 | A1 | 5/2018 |
| WO | WO-2018102562 | A1 | 6/2018 |
| WO | WO-2018129531 | A1 | 7/2018 |
| WO | WO-2019089613 | A1 | 5/2019 |
| WO | WO-2024215560 | A1 | 10/2024 |
| WO | WO-2024215717 | A1 | 10/2024 |

OTHER PUBLICATIONS

"International Application Serial No. PCT/US2024/023095, International Search Report mailed Jul. 9, 2024", 2 pgs.

"International Application Serial No. PCT/US2024/023095, Written Opinion mailed Jul. 9, 2024", 3 pgs.

"International Application Serial No. PCT/US2024/023817, International Search Report mailed Jul. 31, 2024", 3 pgs.

"International Application Serial No. PCT/US2024/023817, Written Opinion mailed Jul. 31, 2024", 8 pgs.

Anpet, Chen, et al., "TensoRF: Tensorial Radiance Fields", arxiv.org, Cornell University Library, 201 Olin Library Cornell University Ithaca, NY 14853, (Nov. 29, 2022), 33 pgs.

Bhatnagar, Bharat, et al., "Multi-Garment Net: Learning to Dress 3D People From Images", IEEE/CVF International Conference on Computer Vision (ICCV), IEEE, (Oct. 27, 2019), 11 pgs.

Loper, Matthew, et al., "SMPL: A Skinned Multi-Person Linear Model", ACM Transactions on Graphics, vol. 34, No. 6, Article 248, [Online]. Retrieved from the Internet: <https://doi.org/10.1145/2816795.2818013>, (Nov. 2015), 16 pages.

Moon, Gyeongsik, et al., "3D Clothed Human Reconstruction in the Wild", In: "17th European Conference on Computer Vision, ECCV, Lecture Notes in Computer Science (13662)", Springer, Berlin, Germany, [Online] Retrieved from the internet: <https://link.springer.com/content/pdf/10.1007/978-3 - 031-20086- 1_11.pdf?pdf=inline%201ink>, (Nov. 11, 2022).

Wojciech, Zielonka, et al., "Instant Volumetric Head Avatars", arxiv.org, Cornell University Library, 201 Olin Library Cornell University Ithaca, NY 14853, (Mar. 23, 2023), 17 pgs.

(56) **References Cited**

OTHER PUBLICATIONS

U.S. Appl. No. 18/134,347, filed Apr. 13, 2023, Animatable Garment Extraction Through Volumetric Reconstruction.
"Bitmoji", Snapchat Support, [Online] Retrieved from the Internet: <URL: https://web.archive.org/web/20190503063620/https://support.snapchat.com/en-US/a/bitmoji>, (captured May 3, 2019), 2 pgs.
"Bitmoji Chrome Extension", [Online] Retrieved from the Internet: <URL: https://web.archive.org/web/20200919024925/https://support.bimoji.com/hc/en-us/articles/360001494066>, (Sep. 19, 2020), 5 pgs.
"Bitmoji Customize text", [Online] Retrieved from the Internet: <URL: https://web.archive.org/web/20210225200456/https://support.bitmoji.com/hc/en-us/articles/360034632291-Customize-Text-on-Bitmoji-Stickers>, (captured Feb. 25, 2021), 3 pgs.
"Bitmoji Family", Snapchat Support, [Online] Retrieved from the Internet: <URL: https://web.archive.org/web/20190503063620/https://support.snapchat.com/en-US/article/bitmoji-family>, (captured May 3, 2019), 4 pgs.
"Instant Comics Starring You & Your Friends", Bitstrips Inc, [Online] Retrieved from the Internet: <URL: https://web.archive.org/web/20150206000940/http://company.bitstrips.com/bitstrips-app.html>, (captured Feb. 6, 2015), 3 pgs.
"Manage Your Bitmoji", Snapchat Support, [Online] Retrieved from the Internet: <URL: https://web.archive.org/web/20190503063620/https://support.snapchat.com/en-US/a/manage-bitmoji>, (captured May 3, 2019), 3 pgs.
"Your Own Personal Emoji", Bitstrips Inc, [Online] Retrieved from the Internet: <URL: https://web.archive.org/web/20150205232004/http://bitmoji.com/>, (captured Feb. 5, 2015), 3 pgs.
Carnahan, Daniel, "Snap is Offering Personalized Video Content Through Bitmoji TV", Business Insider, [Online] Retrieved from the Internet: <URL: https://www.businessinsider.com/snap-offers-personalized-video-content-through-bitmoji-tv-2019-12>, (2019), 10 pgs.
Constine, Josh, "Snapchat launches Bitmoji merch and comic strips starring your avatar", TechCrunch, [Online] Retrieved from the Internet: <URL: https://techcrunch.com/2018/11/13/bitmoji-store/>, (Nov. 13, 2018), 16 pgs.
Constine, Josh, "Snapchat Launches Bitmoji TV: Zany 4-min Cartoons of Your Avatar", TechCrunch, [Online] Retrieved from the Internet: <URL: https://techcrunch.com/2020/01/30/bitmoji-tv/>, (Jan. 30, 2020), 13 pgs.
Macmillan, Douglas, "Snapchat Buys Bitmoji App for More Than $100 Million", The Wallstreet Journal, [Online] Retrieved from the Internet: <URL: https://www.wsj.com/articles/snapchat-buys-bitmoji-app-for-more-than-100-million-1458876017>, (Mar. 25, 2016), 5 pgs.
Newton, Casey, "Your Snapchat friendships now have their own profiles—and merchandise", The Verge, [Online] Retrieved from the Internet: <URL: https://www.theverge.com/2018/11/13/18088772/snapchat-friendship-profiles-bitmoji-merchandise-comics>, (Nov. 13, 2018), 5 pgs.
Ong, Thuy, "Snapchat takes Bitmoji deluxe with hundreds of new customization options", The Verge, [Online] Retrieved from the Internet on Nov. 2, 2018: <URL: https://www.theverge.com/2018/1/30/16949402/bitmoji-deluxe-snapchat-customization>, (Jan. 30, 2018), 2 pgs.
Reign, Ashley, "How To Add My Friend's Bitmoji To My Snapchat", Women.com, [Online] Retrieved from the Internet: <URL: https://www.women.com/ashleyreign/lists/how-to-add-my-friends-bitmoji-to-my-snapchat>, (Jun. 30, 2017), 7 pgs.
Tumbokon, Karen, "Snapchat Update: How To Add Bitmoji To Customizable Geofilters", International Business Times, [Online] Retrieved from the Internet : <URL: https://www.ibtimes.com/snapchat-update-how-add-bitmoji-customizable-geofilters-2448152>, (Nov. 18, 2016), 6 pgs.

* cited by examiner

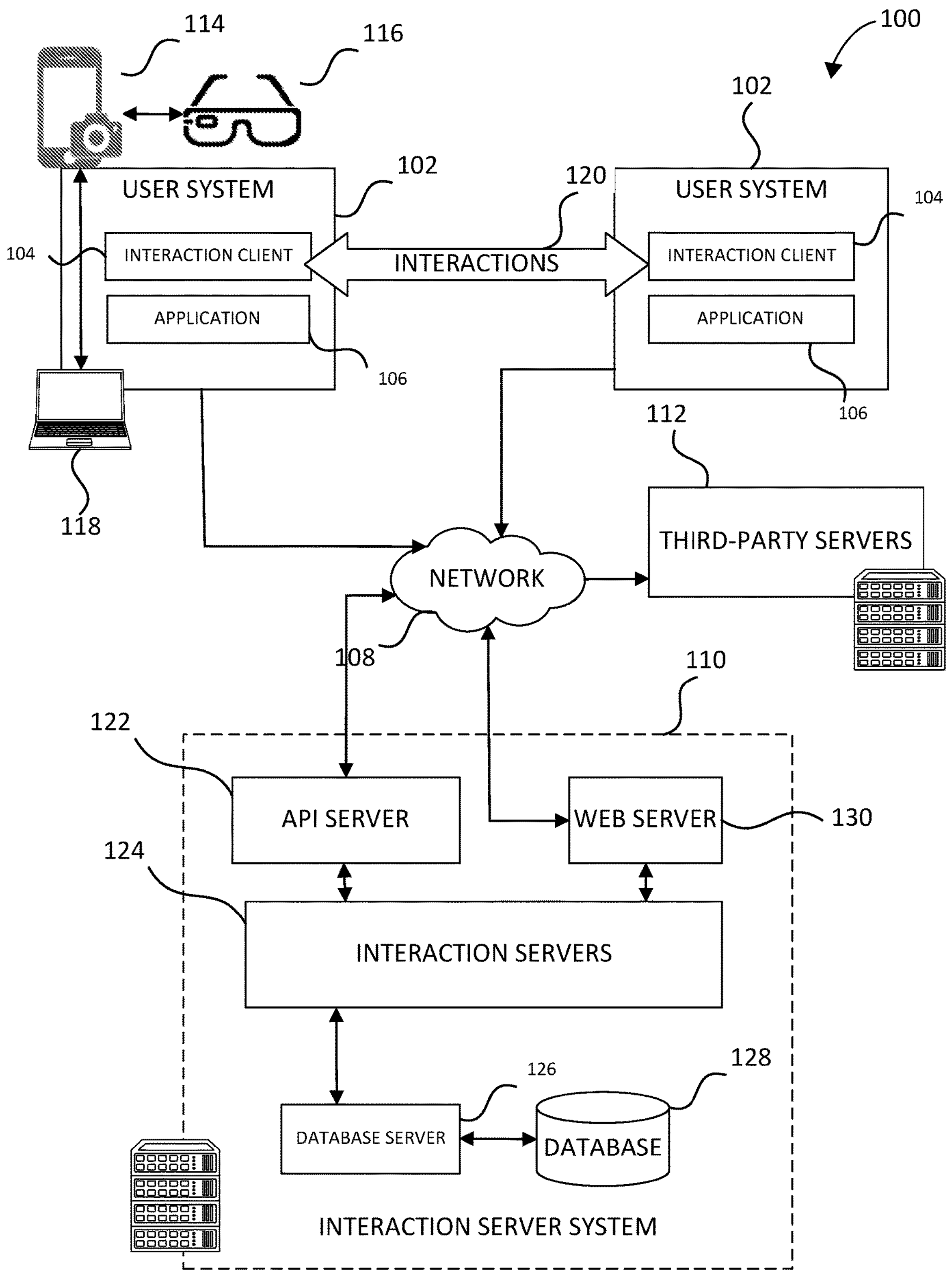
100
114
116
102
USER SYSTEM
INTERACTION CLIENT
APPLICATION
104
106
120
INTERACTIONS
102
USER SYSTEM
INTERACTION CLIENT
APPLICATION
104
106
118
112
THIRD-PARTY SERVERS
NETWORK
108
110
122
API SERVER
WEB SERVER
130
124
INTERACTION SERVERS
126
128
DATABASE SERVER
DATABASE
INTERACTION SERVER SYSTEM

FIG. 1

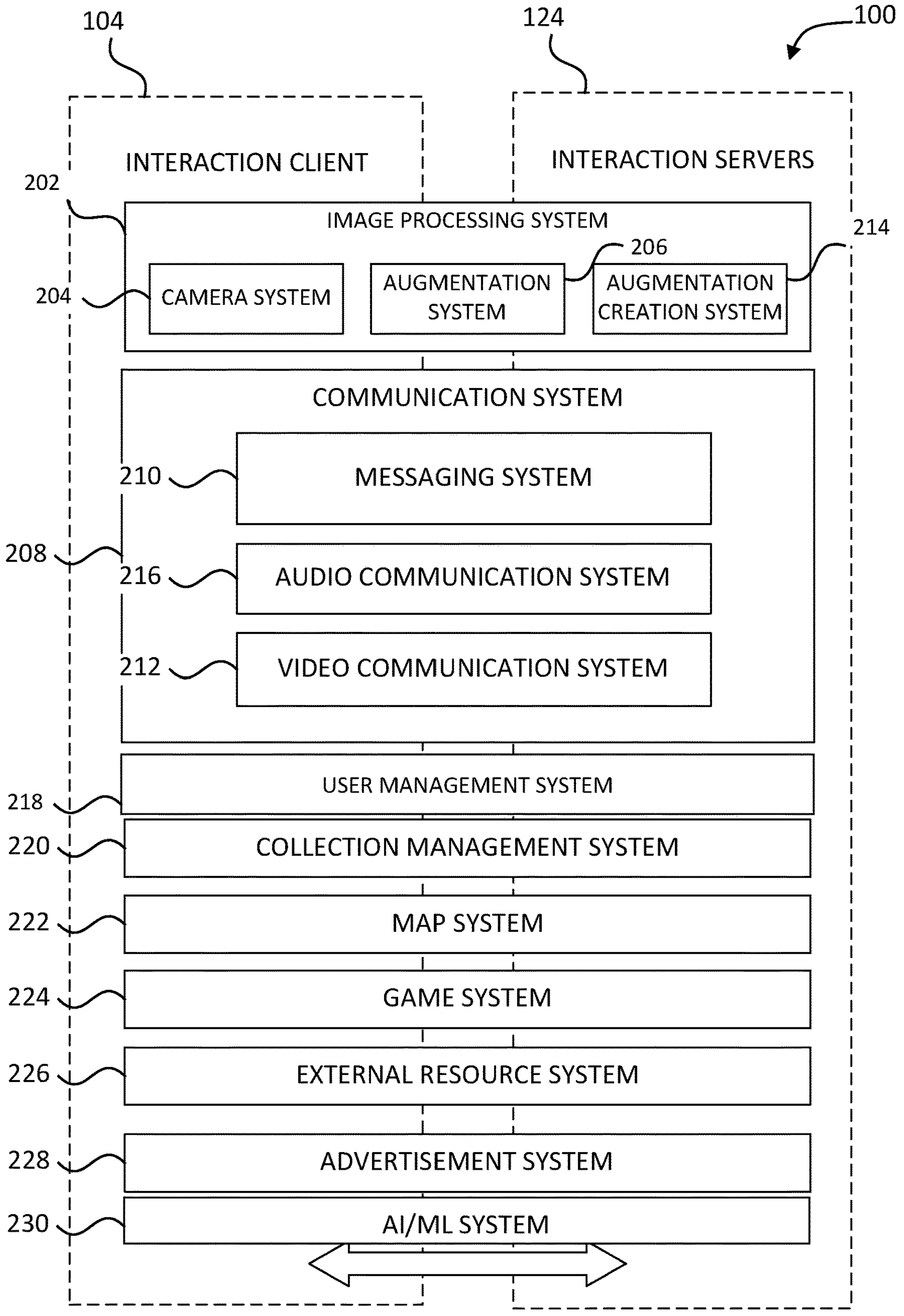
104
124
100
INTERACTION CLIENT
INTERACTION SERVERS
202
IMAGE PROCESSING SYSTEM
206
214
204
CAMERA SYSTEM
AUGMENTATION SYSTEM
AUGMENTATION CREATION SYSTEM
COMMUNICATION SYSTEM
210
MESSAGING SYSTEM
208
216
AUDIO COMMUNICATION SYSTEM
212
VIDEO COMMUNICATION SYSTEM
USER MANAGEMENT SYSTEM
218
220
COLLECTION MANAGEMENT SYSTEM
222
MAP SYSTEM
224
GAME SYSTEM
226
EXTERNAL RESOURCE SYSTEM
228
ADVERTISEMENT SYSTEM
230
AI/ML SYSTEM

FIG. 2

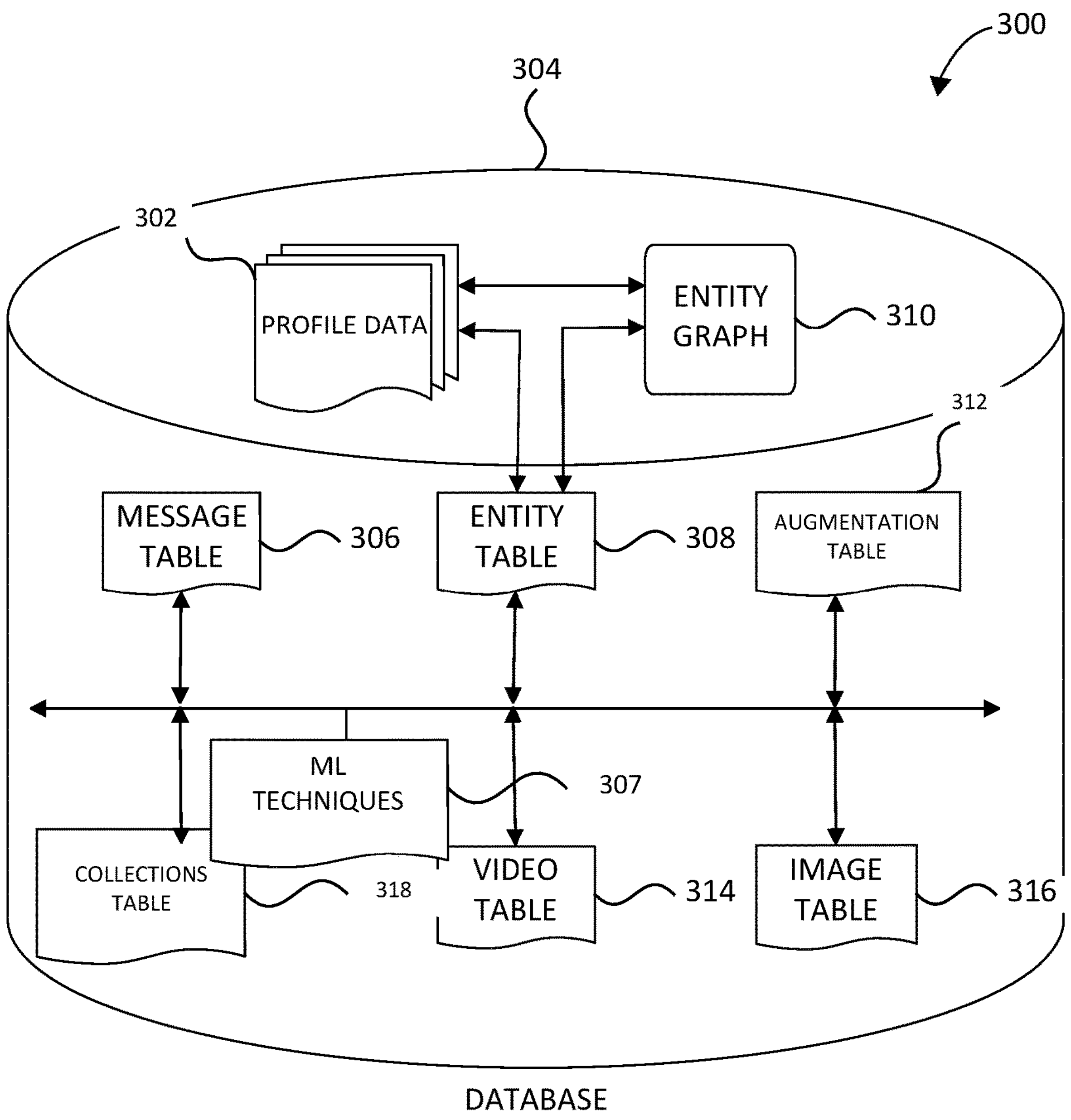
300
304
302
PROFILE DATA
ENTITY GRAPH
310
312
MESSAGE TABLE
306
ENTITY TABLE
308
AUGMENTATION TABLE
ML TECHNIQUES
307
COLLECTIONS TABLE
318
VIDEO TABLE
314
IMAGE TABLE
316
DATABASE

FIG. 3

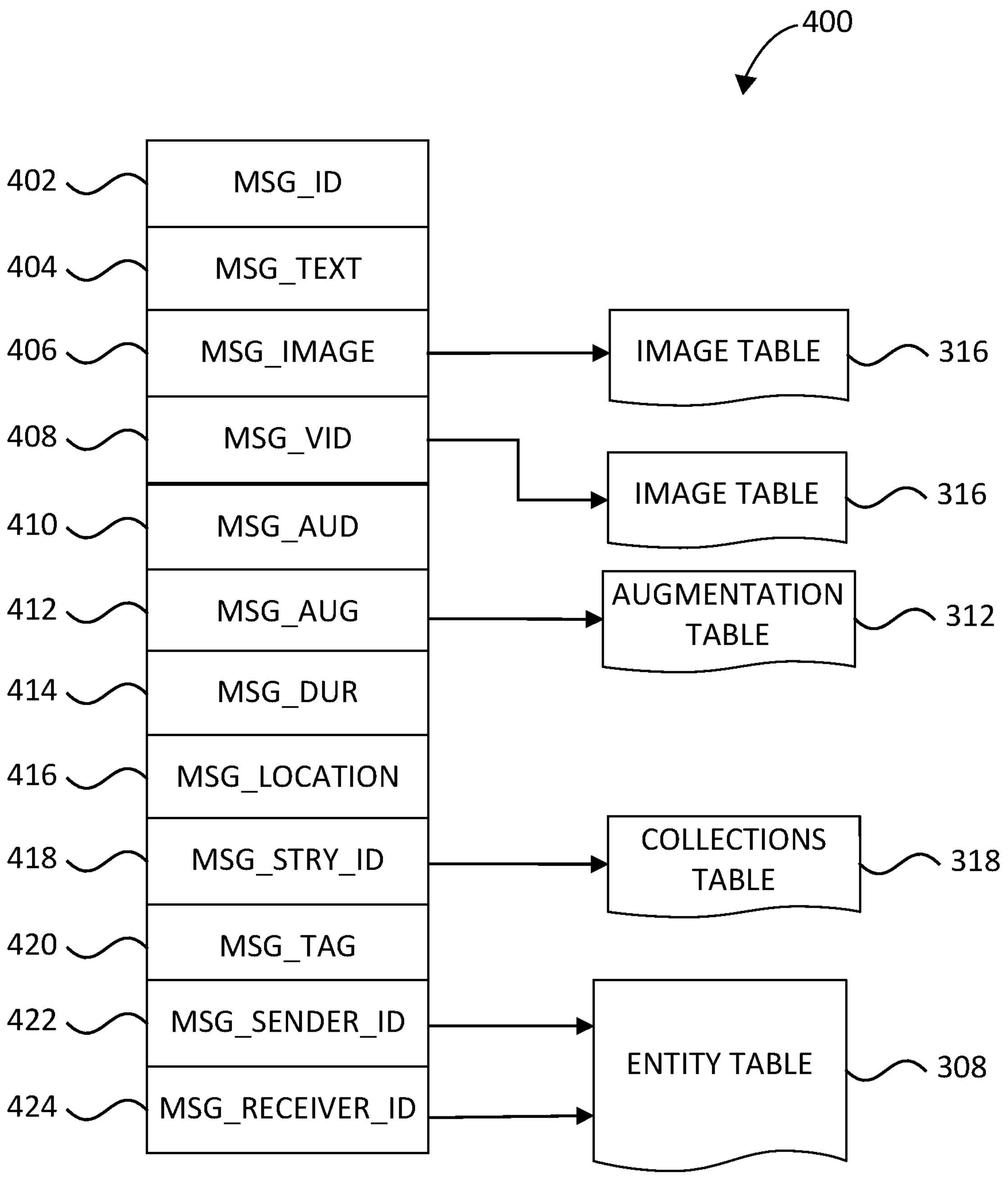
400
402
MSG_ID
404
MSG_TEXT
406
MSG_IMAGE
IMAGE TABLE
316
408
MSG_VID
IMAGE TABLE
316
410
MSG_AUD
412
MSG_AUG
AUGMENTATION TABLE
312
414
MSG_DUR
416
MSG_LOCATION
418
MSG_STRY_ID
COLLECTIONS TABLE
318
420
MSG_TAG
422
MSG_SENDER_ID
424
MSG_RECEIVER_ID
ENTITY TABLE
308

*FIG. 4*

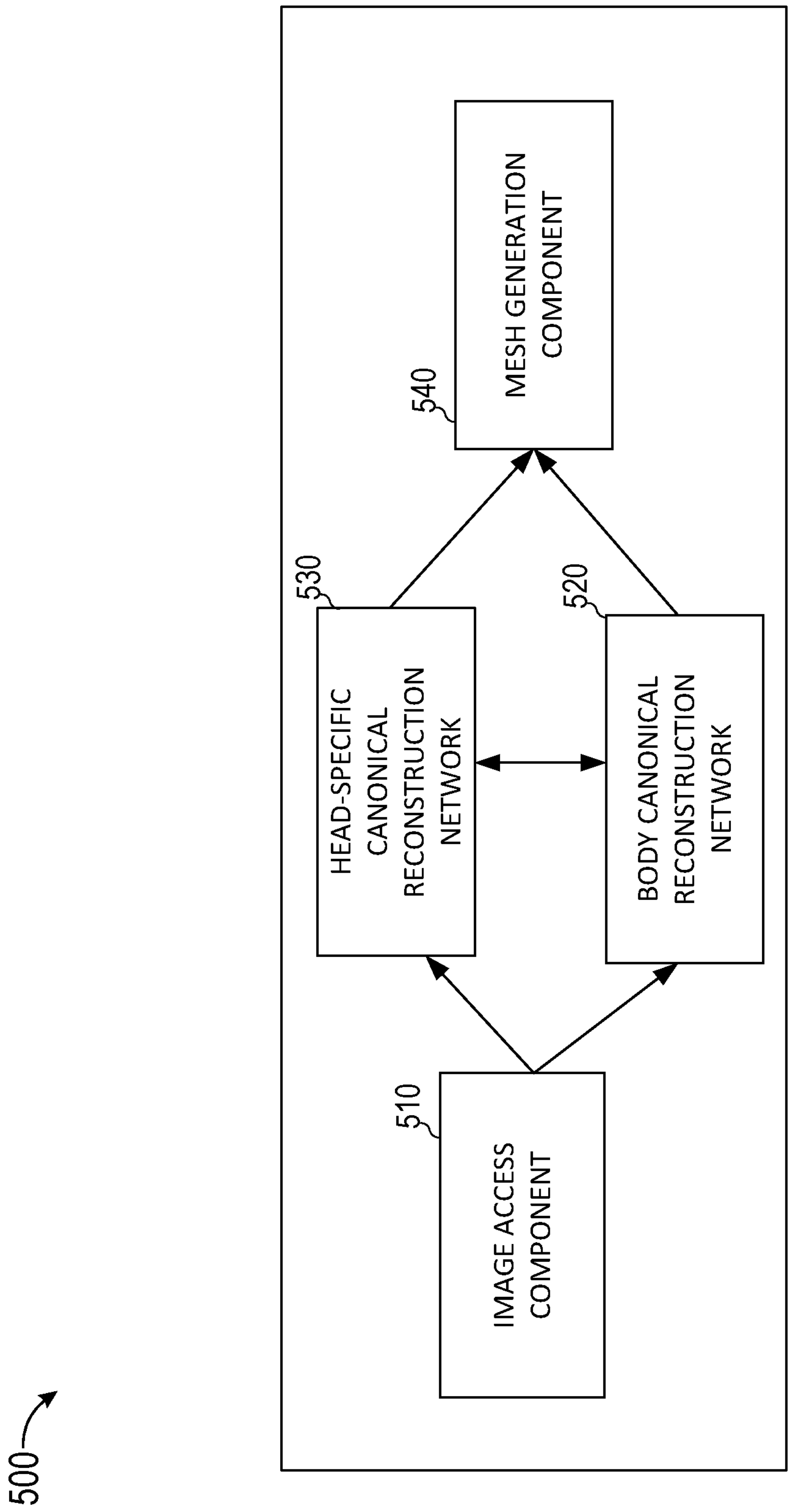
500
510
IMAGE ACCESS COMPONENT
520
BODY CANONICAL RECONSTRUCTION NETWORK
530
HEAD-SPECIFIC CANONICAL RECONSTRUCTION NETWORK
540
MESH GENERATION COMPONENT

FIG. 5

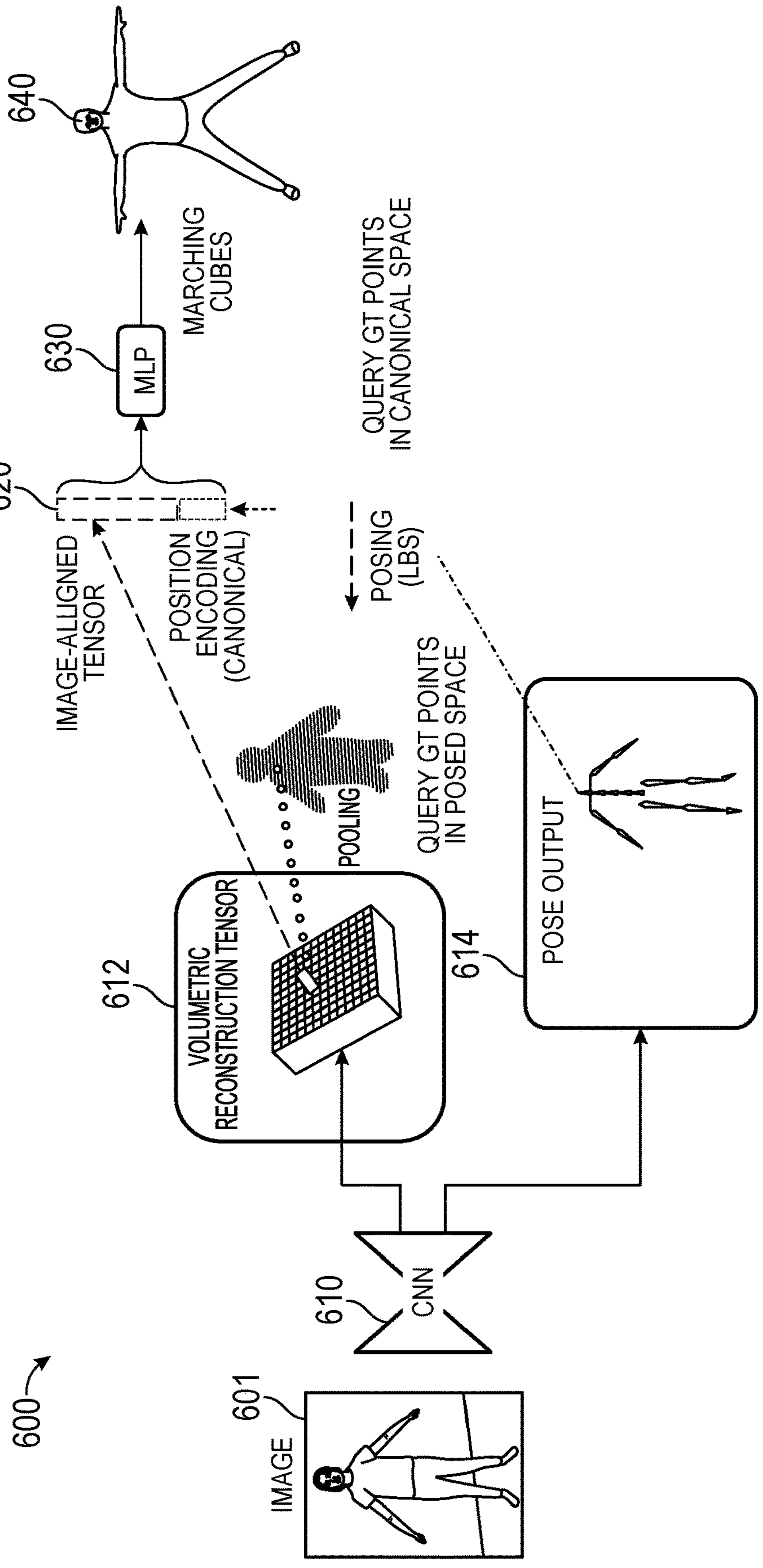
600
IMAGE
601
610
CNN
612
VOLUMETRIC RECONSTRUCTION TENSOR
614
POSE OUTPUT
POOLING
QUERY GT POINTS IN POSED SPACE
IMAGE-ALLIGNED TENSOR
POSITION ENCODING (CANONICAL)
POSING (LBS)
620
630
MLP
MARCHING CUBES
QUERY GT POINTS IN CANONICAL SPACE
640

FIG. 6

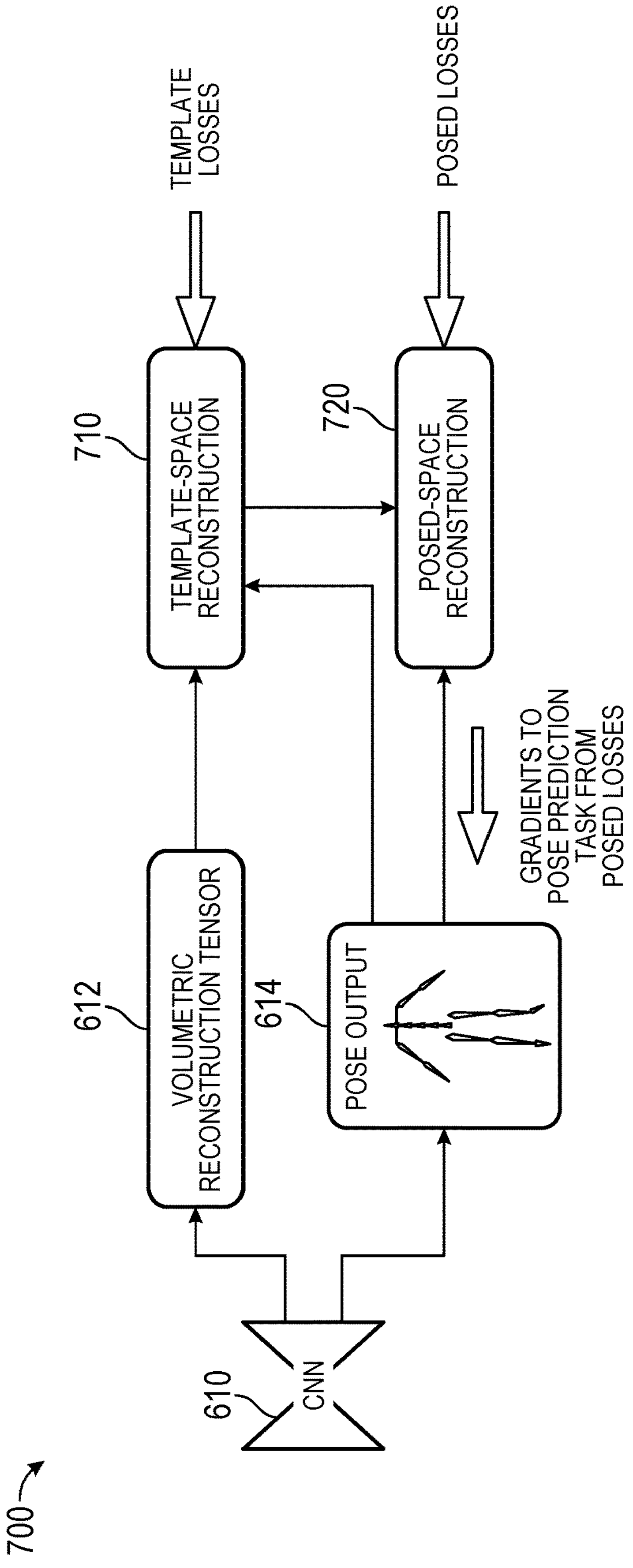
700
610
CNN
612
VOLUMETRIC RECONSTRUCTION TENSOR
614
POSE OUTPUT
710
TEMPLATE-SPACE RECONSTRUCTION
720
POSED-SPACE RECONSTRUCTION
TEMPLATE LOSSES
POSED LOSSES
GRADIENTS TO POSE PREDICTION TASK FROM POSED LOSSES

FIG. 7

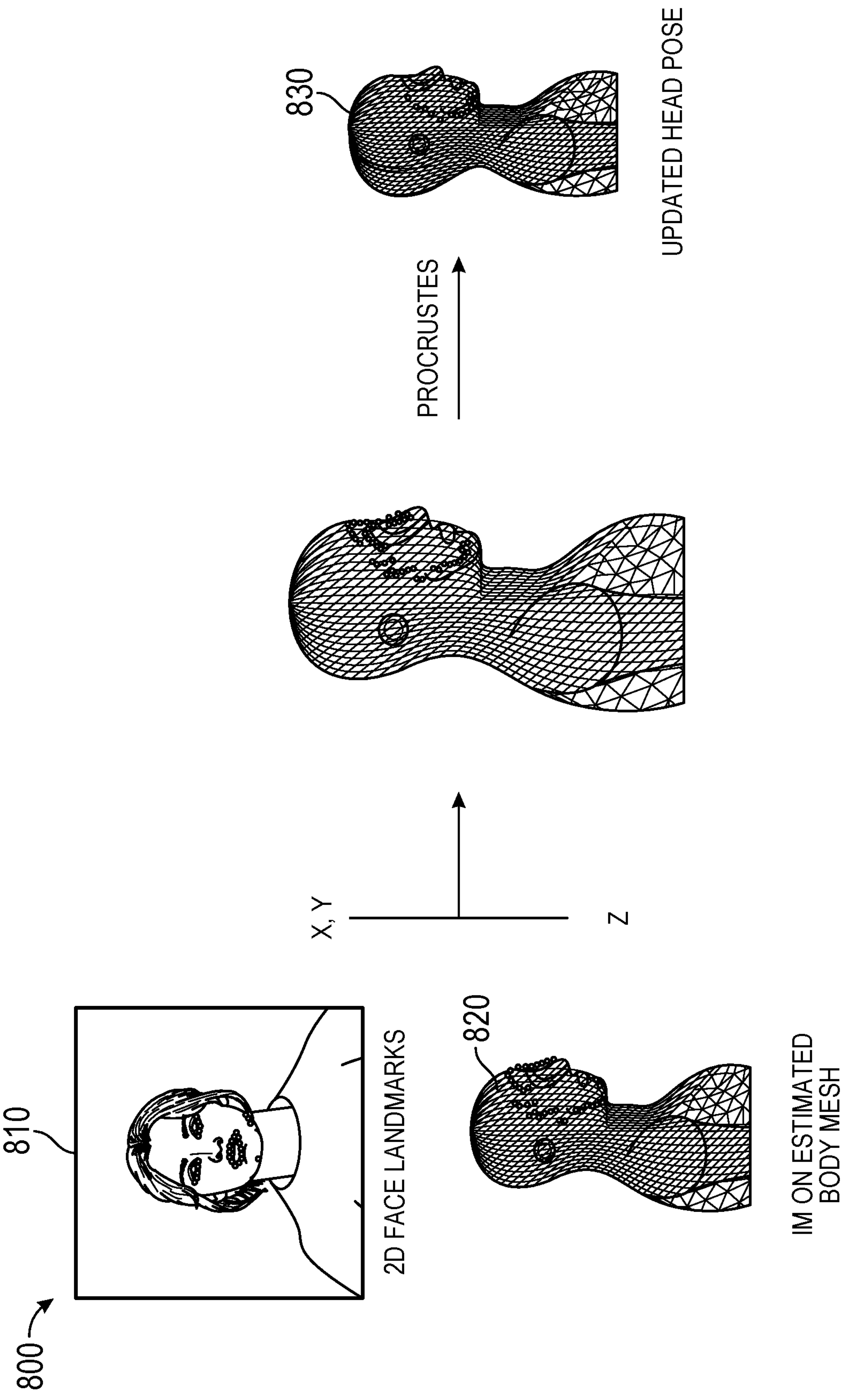
800
810
2D FACE LANDMARKS
820
IM ON ESTIMATED BODY MESH
X, Y
Z
PROCRUSTES
830
UPDATED HEAD POSE

FIG. 8

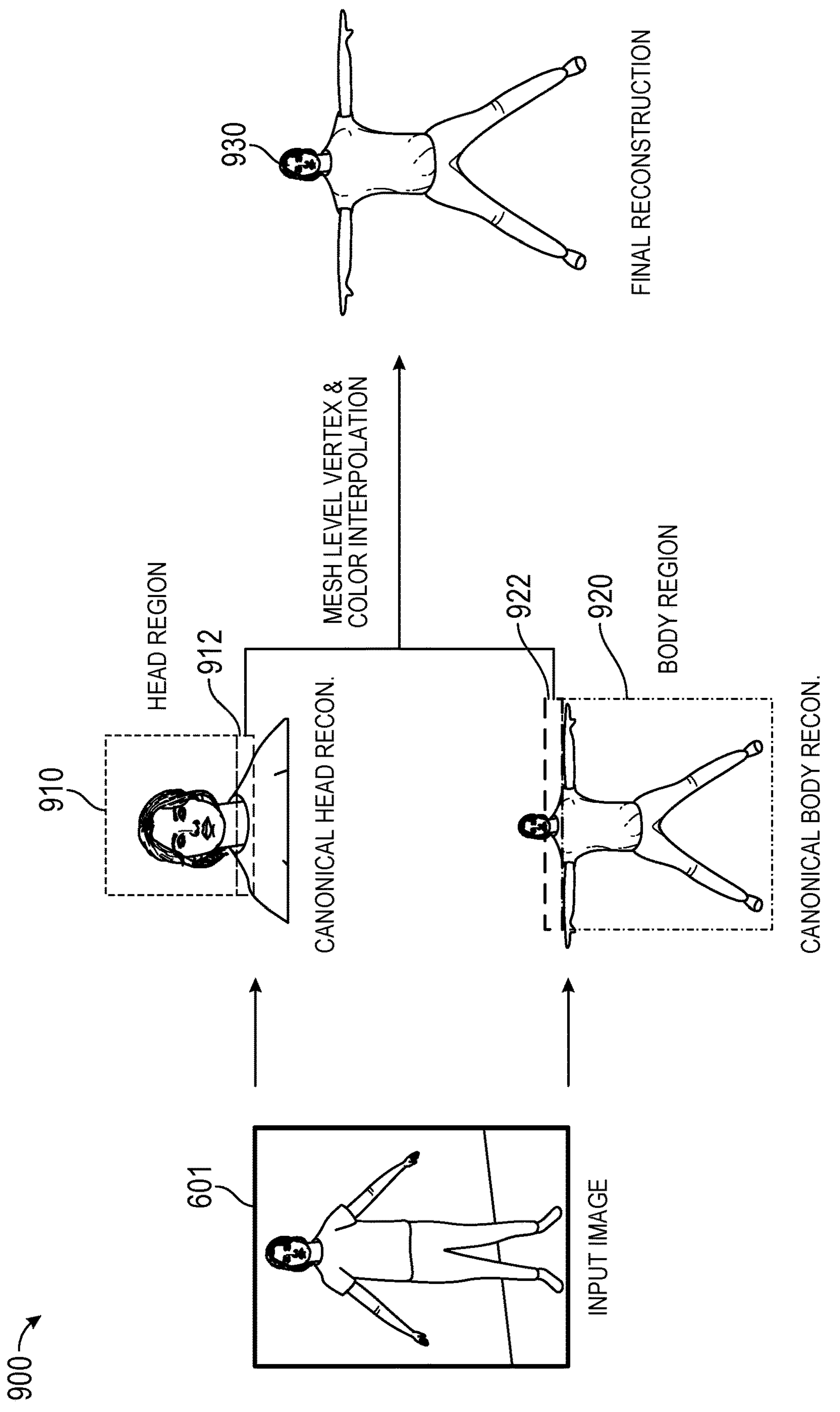
900
601
INPUT IMAGE
910
HEAD REGION
912
CANONICAL HEAD RECON.
922
920
BODY REGION
CANONICAL BODY RECON.
MESH LEVEL VERTEX &
COLOR INTERPOLATION
930
FINAL RECONSTRUCTION

FIG. 9

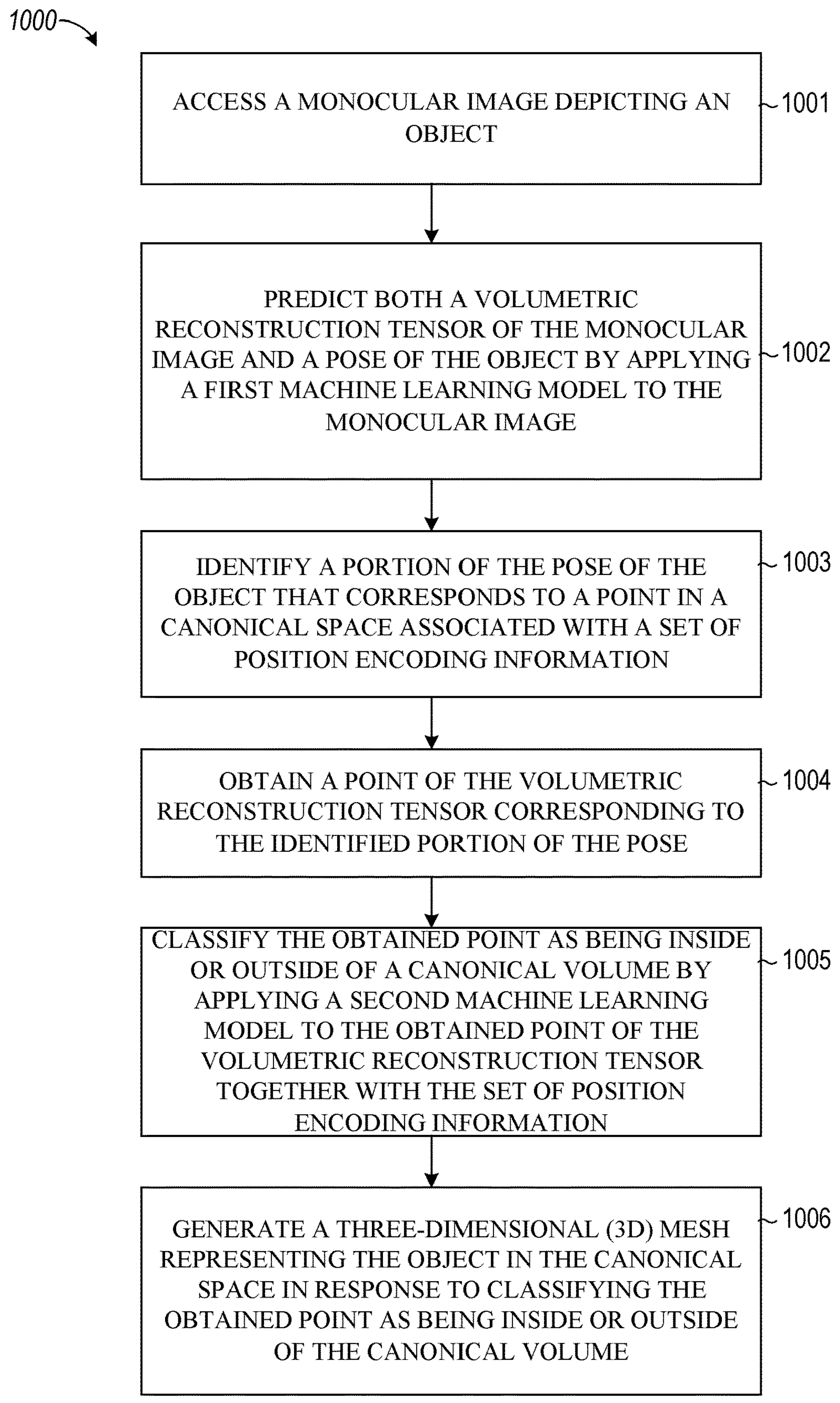
1000
ACCESS A MONOCULAR IMAGE DEPICTING AN OBJECT
1001
PREDICT BOTH A VOLUMETRIC RECONSTRUCTION TENSOR OF THE MONOCULAR IMAGE AND A POSE OF THE OBJECT BY APPLYING A FIRST MACHINE LEARNING MODEL TO THE MONOCULAR IMAGE
1002
IDENTIFY A PORTION OF THE POSE OF THE OBJECT THAT CORRESPONDS TO A POINT IN A CANONICAL SPACE ASSOCIATED WITH A SET OF POSITION ENCODING INFORMATION
1003
OBTAIN A POINT OF THE VOLUMETRIC RECONSTRUCTION TENSOR CORRESPONDING TO THE IDENTIFIED PORTION OF THE POSE
1004
CLASSIFY THE OBTAINED POINT AS BEING INSIDE OR OUTSIDE OF A CANONICAL VOLUME BY APPLYING A SECOND MACHINE LEARNING MODEL TO THE OBTAINED POINT OF THE VOLUMETRIC RECONSTRUCTION TENSOR TOGETHER WITH THE SET OF POSITION ENCODING INFORMATION
1005
GENERATE A THREE-DIMENSIONAL (3D) MESH REPRESENTING THE OBJECT IN THE CANONICAL SPACE IN RESPONSE TO CLASSIFYING THE OBTAINED POINT AS BEING INSIDE OR OUTSIDE OF THE CANONICAL VOLUME
1006

FIG. 10

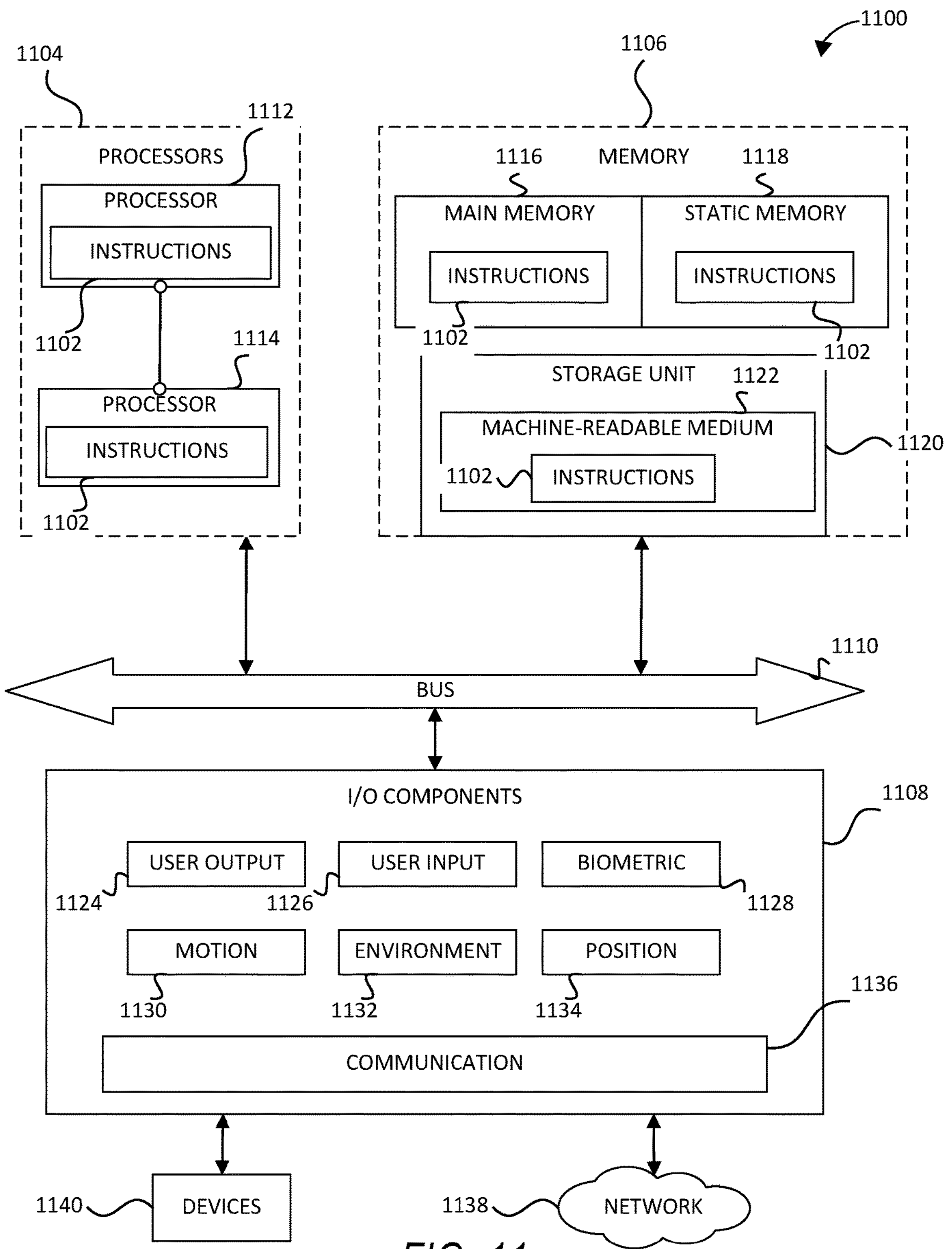
1100
1104
PROCESSORS
1112
PROCESSOR
INSTRUCTIONS
1102
1114
PROCESSOR
INSTRUCTIONS
1102
1106
MEMORY
1116
1118
MAIN MEMORY
INSTRUCTIONS
STATIC MEMORY
INSTRUCTIONS
1102
1102
STORAGE UNIT
1122
MACHINE-READABLE MEDIUM
1102
INSTRUCTIONS
1120
1110
BUS
I/O COMPONENTS
1108
USER OUTPUT
1124
USER INPUT
1126
BIOMETRIC
1128
MOTION
1130
ENVIRONMENT
1132
POSITION
1134
COMMUNICATION
1136
1140
DEVICES
1138
NETWORK

FIG. 11

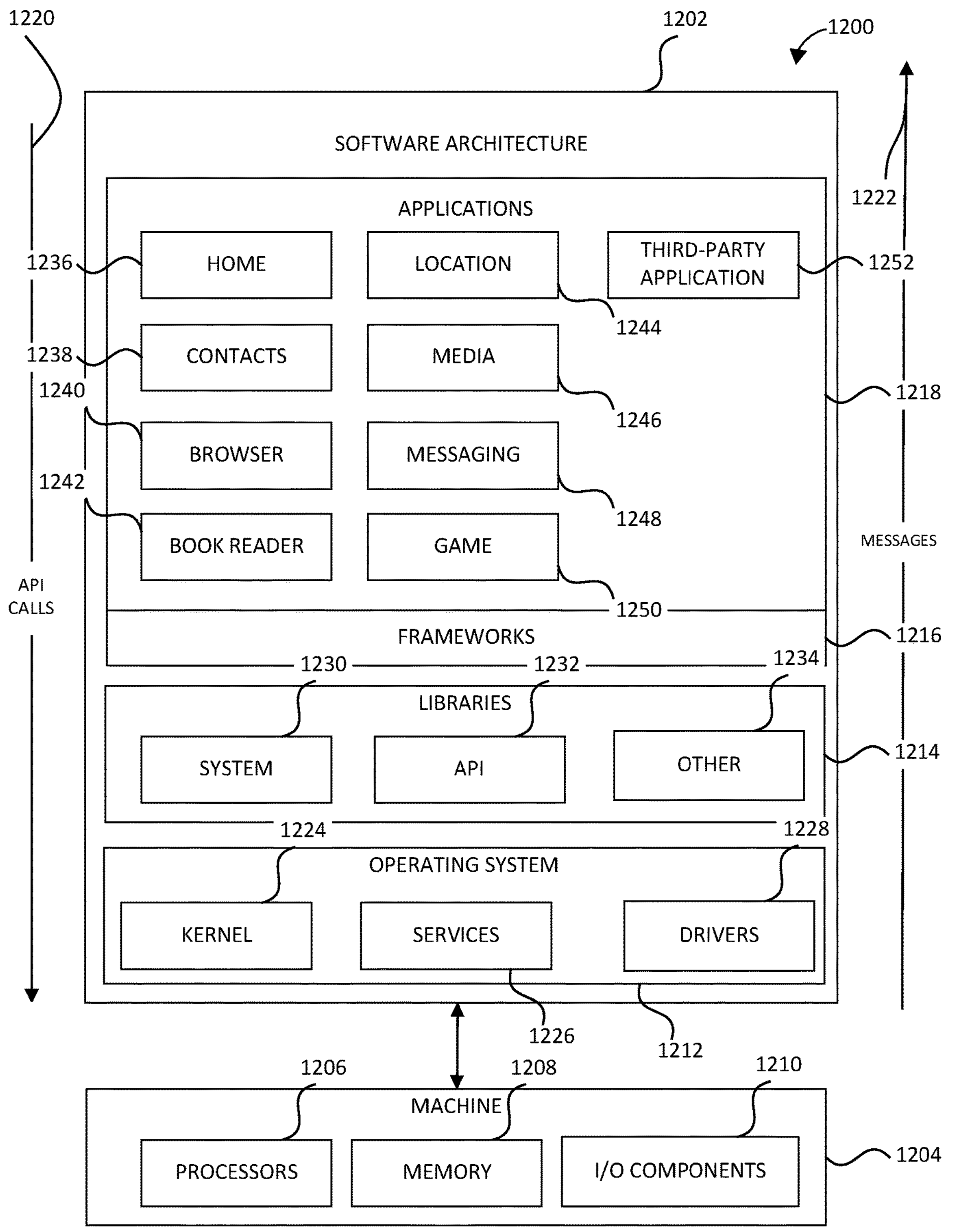
1220
1202
1200
SOFTWARE ARCHITECTURE
APPLICATIONS
1222
1236
HOME
LOCATION
THIRD-PARTY APPLICATION
1252
1244
1238
CONTACTS
MEDIA
1240
1218
1246
BROWSER
MESSAGING
1242
1248
BOOK READER
GAME
MESSAGES
API CALLS
1250
FRAMEWORKS
1216
1230
1232
1234
LIBRARIES
SYSTEM
API
OTHER
1214
1224
1228
OPERATING SYSTEM
KERNEL
SERVICES
DRIVERS
1226
1212
1206
1208
1210
MACHINE
PROCESSORS
MEMORY
I/O COMPONENTS
1204

FIG. 12

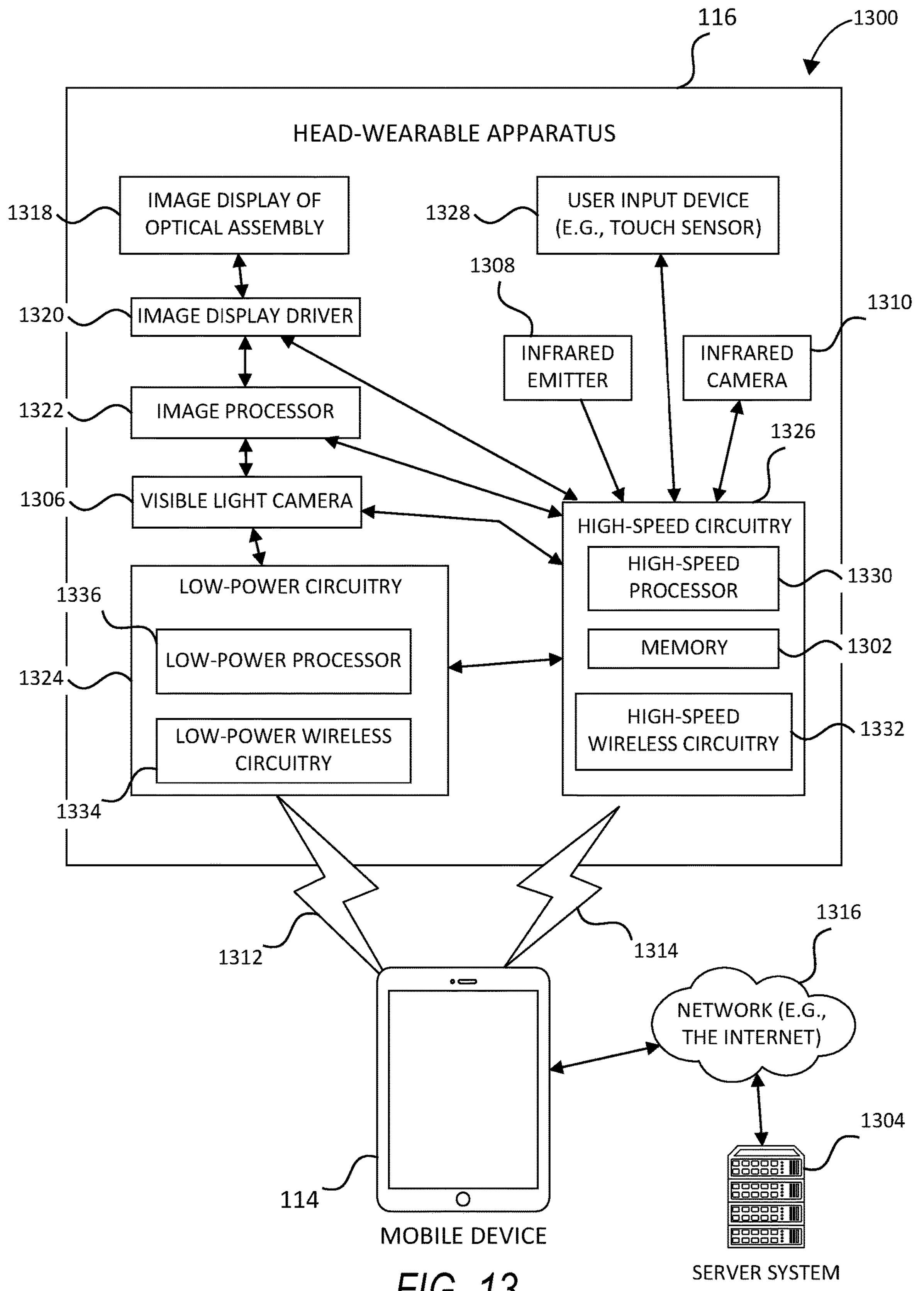
116
1300
HEAD-WEARABLE APPARATUS
1318
IMAGE DISPLAY OF OPTICAL ASSEMBLY
1328
USER INPUT DEVICE (E.G., TOUCH SENSOR)
1308
1310
1320
IMAGE DISPLAY DRIVER
INFRARED EMITTER
INFRARED CAMERA
1322
IMAGE PROCESSOR
1326
1306
VISIBLE LIGHT CAMERA
HIGH-SPEED CIRCUITRY
HIGH-SPEED PROCESSOR
1330
LOW-POWER CIRCUITRY
1336
LOW-POWER PROCESSOR
MEMORY
1302
1324
LOW-POWER WIRELESS CIRCUITRY
HIGH-SPEED WIRELESS CIRCUITRY
1332
1334
1312
1314
1316
NETWORK (E.G., THE INTERNET)
1304
114
MOBILE DEVICE
SERVER SYSTEM

FIG. 13

# BODY MESH RECONSTRUCTION FROM RGB IMAGE

## CLAIM OF PRIORITY

This application claims the benefit of priority to Greece patent application Ser. No. 20230100328, filed on Apr. 13, 2023, which is incorporated herein by reference in its entirety.

## TECHNICAL FIELD

The present disclosure relates to extended reality (XR) devices, such as augmented reality (AR) and/or virtual reality (VR) devices.

## BACKGROUND

AR is a modification of a virtual environment. For example, in VR, a user is completely immersed in a virtual world, whereas in AR, the user is immersed in a world where virtual objects are combined or superimposed on the real world. An AR system aims to generate and present virtual objects that interact realistically with a real-world environment and with each other. Examples of AR applications can include single or multiple player video games, instant messaging systems, and the like.

## BRIEF DESCRIPTION OF THE SEVERAL VIEWS OF THE DRAWINGS

In the drawings, which are not necessarily drawn to scale, like numerals may describe similar components in different views. To easily identify the discussion of any particular element or act, the most significant digit or digits in a reference number refer to the figure number in which that element is first introduced. Some nonlimiting examples are illustrated in the figures of the accompanying drawings in which:

FIG. **1** is a diagrammatic representation of a networked environment in which the present disclosure may be deployed, according to some examples.

FIG. **2** is a diagrammatic representation of a messaging system that has both client-side and server-side functionality, according to some examples.

FIG. **3** is a diagrammatic representation of a data structure as maintained in a database, according to some examples.

FIG. **4** is a diagrammatic representation of a message, according to some examples.

FIG. **5** is a diagrammatic representation of mesh generation system, in accordance with some examples.

FIG. **6** is a diagrammatic representation of a full body canonical space reconstruction system, in accordance with some examples.

FIG. **7** is a diagrammatic representation of training losses for the full body canonical space reconstruction system, in accordance with some examples.

FIG. **8** is a diagrammatic representation of head pose refinement for the full body canonical space reconstruction system, in accordance with some examples.

FIG. **9** is a diagrammatic representation of a mesh generation component of the full body canonical space reconstruction system, in accordance with some examples.

FIG. **10** is a flowchart illustrating example operations of the mesh generation system, in accordance with some examples.

FIG. **11** is a diagrammatic representation of a machine in the form of a computer system within which a set of instructions may be executed to cause the machine to perform any one or more of the methodologies discussed herein, in accordance with some examples.

FIG. **12** is a block diagram showing a software architecture within which examples may be implemented.

FIG. **13** illustrates a system in which a head-wearable apparatus may be implemented, in accordance with some examples.

## DETAILED DESCRIPTION

The description that follows includes systems, methods, techniques, instruction sequences, and computing machine program products that embody illustrative examples of the disclosure. In the following description, for the purposes of explanation, numerous specific details are set forth in order to provide an understanding of various examples. It will be evident, however, to those skilled in the art, that examples may be practiced without these specific details. In general, well-known instruction instances, protocols, structures, and techniques are not necessarily shown in detail.

Typically, VR and AR systems display images representing a given user by capturing an image of the user and, in addition, obtaining a depth map using a depth sensor of the real-world human body depicted in the image. By processing the depth map and the image together, the VR and AR systems can detect positioning of the user in the image and can appropriately modify the user or background in the images. While such systems work well, the need for a depth sensor limits the scope of their applications. This is because adding depth sensors to user devices for the purpose of modifying images increases the overall cost and complexity of the devices, making them less attractive and more difficult to implement in a mobile device setting.

Certain systems estimate three-dimensional (3D) meshes of persons depicted in images to provide AR/VR experiences. Human 3D pose understanding is essential to human-computer interaction, motion capture, action recognition, and augmented and virtual reality (AR/VR). Human mesh reconstruction has received increased attention recently based on the premise that information beyond the 3D skeleton can unlock new experiences that require detailed estimation of 3D human geometry, such as avatar construction and telepresence for VR or visual effects and virtual try-on for AR.

Despite the rapid progress in 3D mesh reconstruction technology, the meshes resulting from current systems are still far from being pixel-accurate when projected back to the image domain. Some conventional systems predict the 3D mesh through a parametric human model using an already cropped image. A convolutional encoder is used to minimize the 2D joints' reprojection error, while a discriminator decides if the 3D parameters are plausible. Such systems are incredibly complex to implement, such as on mobile device platforms, and will still produce results that are not pixel-accurate. Certain conventional systems generate a 3D mesh by predicting the full body 3D reconstruction of an object depicted in an image using multiple networks that are each trained independent of one another. For example, the conventional systems can use a first machine learning model to generate a pose of an object depicted in an image, a second machine learning model to generate a pixel representation of the object depicted in the image, and yet a third machine learning model to determine whether pixels of the object correspond to a canonical space volume representing the object. Because three individual machine learning models are used in these conventional systems to generate independent predictions, results can include multiple instances of disagreement, poor training, and lack of efficiency when deployed on user devices, such as mobile platforms. Even still, these systems fail to provide pixel-accurate representations of both the entire body of the users and facial aspects of the users and usually produce many blurry portions of the meshes specifically in facial regions.

The disclosed techniques seek to improve the way in which a 3D mesh is generated for one or more real-world objects (e.g., real-world persons) depicted in an image or video. The disclosed techniques predict both a volumetric reconstruction tensor of the monocular image and a pose of an object by applying a first machine learning model to a monocular image that depicts the object. The disclosed techniques identify a portion of the pose of the object that corresponds to a point in a canonical space associated with a set of position encoding information. The disclosed techniques obtain a point of the volumetric reconstruction tensor corresponding to the identified portion of the pose. The disclosed techniques classify the obtained point as being inside or outside of a canonical volume by applying a second machine learning model to the obtained point of the volumetric reconstruction tensor together with the set of position encoding information. The disclosed techniques generate a 3D mesh representing the object in the canonical space.

In addition, the disclosed techniques apply a similar process to generate a pixel-accurate facial mesh of the object depicted in the image. Particularly, the disclosed techniques crop a portion of the monocular image corresponding to a head of the object and predict a head-specific canonical space reconstruction of the object by applying a head-specific canonical network to the cropped portion based on generated facial landmarks of the object. The disclosed techniques then combine the head-specific canonical space reconstruction with the canonical volume corresponding to the object to generate a pixel-accurate canonical volume reconstruction of the object. In some cases, the disclosed techniques smoothly deform a region of overlap between a full body canonical space reconstruction of the object and the head-specific canonical space reconstruction to generate the pixel-accurate canonical volume reconstruction. This pixel-accurate canonical volume reconstruction can be used to generate and provide a bottom-up estimate of 3D mesh geometry that can be projected back to the image in a pixel-accurate manner.

This simplifies the process of adding AR graphics to an image or video, which significantly reduces design constraints and costs in generating such AR graphics and decreases the amount of processing complexities and power and memory requirements. This also improves the illusion of the AR graphics being part of a real-world environment depicted in an image or video that depicts real-world objects. This enables seamless and efficient addition of AR graphics to an underlying image or video in real time on small-scale mobile devices. The disclosed techniques can be applied exclusively or mostly on a mobile device without the need for the mobile device to send images/videos to a server. In other examples, the disclosed techniques are applied exclusively or mostly on a remote server or can be divided between a mobile device and a server.

This improves the overall experience of the user in using the electronic device. Also, by providing such AR experiences without using a depth sensor, the overall amount of system resources needed to accomplish a task is reduced. As used herein, "article of clothing," "fashion item," and "garment" are used interchangeably and should be understood to have the same meaning. Article of clothing, garment, or fashion item can include a shirt, skirt, dress, shoes, purse, furniture item, household item, eyewear, eyeglasses, AR logo, AR emblem, pants, shorts, jacket, t-shirt, blouse, glasses, jewelry, earrings, bunny ears, a hat, earmuffs, or any other suitable item or object.

## Networked Computing Environment

FIG. **1** is a block diagram showing an example interaction system **100** for facilitating interactions (e.g., exchanging text messages, conducting text audio and video calls, or playing games) over a network. The interaction system **100** includes multiple user systems **102**, each of which hosts multiple applications, including an interaction client **104** and other applications **106**. Each interaction client **104** is communicatively coupled, via one or more communication networks including a network **108** (e.g., the Internet), to other instances of the interaction client **104** (e.g., hosted on respective other user systems **102**), an interaction server system **110** and third-party servers **112**). An interaction client **104** can also communicate with locally hosted applications **106** using Applications Program Interfaces (APIs).

Each user system **102** may include multiple user devices, such as a mobile device **114**, head-wearable apparatus **116**, and a computer client device **118** that are communicatively connected to exchange data and messages.

An interaction client **104** interacts with other interaction clients **104** and with the interaction server system **110** via the network **108**. The data exchanged between the interaction clients **104** (e.g., interactions **120**) and between the interaction clients **104** and the interaction server system **110** includes functions (e.g., commands to invoke functions) and payload data (e.g., text, audio, video, or other multimedia data).

The interaction server system **110** provides server-side functionality via the network **108** to the interaction clients **104**. While certain functions of the interaction system **100** are described herein as being performed by either an interaction client **104** or by the interaction server system **110**, the location of certain functionality either within the interaction client **104** or the interaction server system **110** may be a design choice. For example, it may be technically preferable to initially deploy particular technology and functionality within the interaction server system **110** but to later migrate this technology and functionality to the interaction client **104** where a user system **102** has sufficient processing capacity.

The interaction server system **110** supports various services and operations that are provided to the interaction clients **104**. Such operations include transmitting data to, receiving data from, and processing data generated by the interaction clients **104**. This data may include message content, client device information, geolocation information, media augmentation and overlays, message content persistence conditions, entity relationship information, and live event information. Data exchanges within the interaction system **100** are invoked and controlled through functions available via user interfaces of the interaction clients **104**.

Turning now specifically to the interaction server system **110**, an API server **122** is coupled to and provides programmatic interfaces to interaction servers **124**, making the functions of the interaction servers **124** accessible to interaction clients **104**, other applications **106**, and third-party server **112**. The interaction servers **124** are communicatively coupled to a database server **126**, facilitating access to a database **128** that stores data associated with interactions processed by the interaction servers **124**. Similarly, a web server **130** is coupled to the interaction servers **124** and provides web-based interfaces to the interaction servers **124**. To this end, the web server **130** processes incoming network requests over Hypertext Transfer Protocol (HTTP) and several other related protocols.

The API server **122** receives and transmits interaction data (e.g., commands and message payloads) between the interaction servers **124** and the user systems **102** (and, for example, interaction clients **104** and other application **106**) and the third-party server **112**. Specifically, the API server **122** provides a set of interfaces (e.g., routines and protocols) that can be called or queried by the interaction client **104** and other applications **106** to invoke functionality of the interaction servers **124**. The API server **122** exposes various functions supported by the interaction servers **124**, including account registration; login functionality; the sending of interaction data, via the interaction servers **124**, from a particular interaction client **104** to another interaction client **104**; the communication of media files (e.g., images or video) from an interaction client **104** to the interaction servers **124**; the settings of a collection of media data (e.g., a story); the retrieval of a list of friends of a user of a user system **102**; the retrieval of messages and content; the addition and deletion of entities (e.g., friends) to an entity relationship graph (e.g., the entity graph **310**); the location of friends within an entity relationship graph; and opening an application event (e.g., relating to the interaction client **104**).

The interaction servers **124** host multiple systems and subsystems, described below with reference to FIG. **2**.

## Linked Applications

Returning to the interaction client **104**, features and functions of an external resource (e.g., a linked application **106** or applet) are made available to a user via an interface of the interaction client **104**. In this context, "external" refers to the fact that the application **106** or applet is external to the interaction client **104**. The external resource is often provided by a third party but may also be provided by the creator or provider of the interaction client **104**. The interaction client **104** receives a user selection of an option to launch or access features of such an external resource. The external resource may be the application **106** installed on the user system **102** (e.g., a "native app"), or a small-scale version of the application (e.g., an "applet") that is hosted on the user system **102** or remote of the user system **102** (e.g., on third-party servers **112**). The small-scale version of the application includes a subset of features and functions of the application (e.g., the full-scale, native version of the application) and is implemented using a markup-language document. In some examples, the small-scale version of the application (e.g., an "applet") is a web-based, markup-language version of the application and is embedded in the interaction client **104**. In addition to using markup-language documents (e.g., a .*ml file), an applet may incorporate a scripting language (e.g., a .*js file or a .json file) and a style sheet (e.g., a .*ss file).

In response to receiving a user selection of the option to launch or access features of the external resource, the interaction client **104** determines whether the selected external resource is a web-based external resource or a locally-installed application **106**. In some cases, applications **106** that are locally installed on the user system **102** can be launched independently of and separately from the interaction client **104**, such as by selecting an icon corresponding to the application **106** on a home screen of the user system **102**. Small-scale versions of such applications can be launched or accessed via the interaction client **104** and, in some examples, no or limited portions of the small-scale application can be accessed outside of the interaction client **104**. The small-scale application can be launched by the interaction client **104** receiving, from a third-party server **112** for example, a markup-language document associated with the small-scale application and processing such a document.

In response to determining that the external resource is a locally-installed application **106**, the interaction client **104** instructs the user system **102** to launch the external resource by executing locally-stored code corresponding to the external resource. In response to determining that the external resource is a web-based resource, the interaction client **104** communicates with the third-party servers **112** (for example) to obtain a markup-language document corresponding to the selected external resource. The interaction client **104** then processes the obtained markup-language document to present the web-based external resource within a user interface of the interaction client **104**.

The interaction client **104** can notify a user of the user system **102**, or other users related to such a user (e.g., "friends"), of activity taking place in one or more external resources. For example, the interaction client **104** can provide participants in a conversation (e.g., a chat session) in the interaction client **104** with notifications relating to the current or recent use of an external resource by one or more members of a group of users. One or more users can be invited to join in an active external resource or to launch a recently used but currently inactive (in the group of friends) external resource. The external resource can provide participants in a conversation, each using respective interaction clients **104**, with the ability to share an item, status, state, or location in an external resource in a chat session with one or more members of a group of users. The shared item may be an interactive chat card with which members of the chat can interact, for example, to launch the corresponding external resource, view specific information within the external resource, or take the member of the chat to a specific location or state within the external resource. Within a given external resource, response messages can be sent to users on the interaction client **104**. The external resource can selectively include different media items in the responses, based on a current context of the external resource.

The interaction client **104** can present a list of the available external resources (e.g., applications **106** or applets) to a user to launch or access a given external resource. This list can be presented in a context-sensitive menu. For example, the icons representing different ones of the application **106** (or applets) can vary based on how the menu is launched by the user (e.g., from a conversation interface or from a non-conversation interface).

## System Architecture

FIG. **2** is a block diagram illustrating further details regarding the interaction system **100**, according to some examples. Specifically, the interaction system **100** is shown to comprise the interaction client **104** and the interaction servers **124**. The interaction system **100** embodies multiple subsystems, which are supported on the client-side by the interaction client **104** and on the server-side by the interaction servers **124**. Example subsystems are discussed below and can include a mesh generation system **500** that generates a mesh of an object depicted in a two-dimensional (2D) image, such as a user, to enable a user to control an interaction client/application/XR experience. An illustrative implementation of the mesh generation system **500** is shown and described in connection with FIG. **5** below.

In some examples, these subsystems are implemented as microservices. A microservice subsystem (e.g., a microservice application) may have components that enable it to operate independently and communicate with other services. Example components of a microservice subsystem may include:

- Function logic: The function logic implements the functionality of the microservice subsystem, representing a specific capability or function that the microservice provides.
- API interface: Microservices may communicate with other components through well-defined APIs or interfaces, using lightweight protocols such as REST or messaging. The API interface defines the inputs and outputs of the microservice subsystem and how it interacts with other microservice subsystems of the interaction system **100**.
- Data storage: A microservice subsystem may be responsible for its own data storage, which may be in the form of a database, cache, or other storage mechanism (e.g., using the database server **126** and database **128**). This enables a microservice subsystem to operate independently of other microservices of the interaction system **100**.
- Service discovery: Microservice subsystems may find and communicate with other microservice subsystems of the interaction system **100**. Service discovery mechanisms enable microservice subsystems to locate and communicate with other microservice subsystems in a scalable and efficient way.
- Monitoring and logging: Microservice subsystems may need to be monitored and logged in order to ensure availability and performance. Monitoring and logging mechanisms enable the tracking of health and performance of a microservice subsystem.

In some examples, the interaction system **100** may employ a monolithic architecture, a service-oriented architecture (SOA), a function-as-a-service (FaaS) architecture, or a modular architecture:

An image processing system **202** provides various functions that enable a user to capture and augment (e.g., annotate or otherwise modify or edit) media content associated with a message.

A camera system **204** includes control software (e.g., in a camera application) that interacts with and controls camera hardware (e.g., directly or via operating system controls) of the user system **102** to modify and augment real-time images captured and displayed via the interaction client **104**.

An augmentation system **206** provides functions related to the generation and publishing of augmentations (e.g., media overlays) for images captured in real-time by cameras of the user system **102** or retrieved from memory of the user system **102**. For example, the augmentation system **206** operatively selects, presents, and displays media overlays (e.g., an image filter or an image lens) to the interaction client **104** for the augmentation of real-time images received via the camera system **204** or stored images retrieved from memory **1302** (shown in FIG. **13**) of a user system **102**. These augmentations are selected by the augmentation system **206** and presented to a user of an interaction client **104**, based on a number of inputs and data, such as, for example:

- Geolocation of the user system **102**; and
- Entity relationship information of the user of the user system **102**.

An augmentation may include audio and visual content and visual effects. Examples of audio and visual content include pictures, texts, logos, animations, and sound effects. An example of a visual effect includes color overlaying. The audio and visual content or the visual effects can be applied to a media content item (e.g., a photo or video) at user system **102** for communication in a message, or applied to video content, such as a video content stream or feed transmitted from an interaction client **104**. As such, the image processing system **202** may interact with, and support, the various subsystems of a communication system **208**, such as a messaging system **210** and a video communication system **212**.

A media overlay may include text or image data that can be overlaid on top of a photograph taken by the user system **102** or a video stream produced by the user system **102**. In some examples, the media overlay may be a location overlay (e.g., Venice beach), a name of a live event, or a name of a merchant overlay (e.g., Beach Coffee House). In further examples, the image processing system **202** uses the geolocation of the user system **102** to identify a media overlay that includes the name of a merchant at the geolocation of the user system **102**. The media overlay may include other indicia associated with the merchant. The media overlays may be stored in the databases **128** and accessed through the database server **126**.

The image processing system **202** provides a user-based publication platform that enables users to select a geolocation on a map and upload content associated with the selected geolocation. The user may also specify circumstances under which a particular media overlay should be offered to other users. The image processing system **202** generates a media overlay that includes the uploaded content and associates the uploaded content with the selected geolocation.

An augmentation creation system **214** supports AR developer platforms and includes an application for content creators (e.g., artists and developers) to create and publish augmentations (e.g., AR experiences) of the interaction client **104**. The augmentation creation system **214** provides a library of built-in features and tools to content creators including, for example, custom shaders, tracking technology, and templates.

In some examples, the augmentation creation system **214** provides a merchant-based publication platform that enables merchants to select a particular augmentation associated with a geolocation via a bidding process. For example, the augmentation creation system **214** associates a media overlay of the highest bidding merchant with a corresponding geolocation for a predefined amount of time.

A communication system **208** is responsible for enabling and processing multiple forms of communication and interaction within the interaction system **100** and includes a messaging system **210**, an audio communication system **216**, and a video communication system **212**. The messaging system **210** is responsible for enforcing the temporary or time-limited access to content by the interaction clients **104**. The messaging system **210** incorporates multiple timers (e.g., within a user management system **218**) that, based on duration and display parameters associated with a message or collection of messages (e.g., a story), selectively enable access (e.g., for presentation and display) to messages and associated content via the interaction client **104**. The audio communication system **216** enables and supports audio communications (e.g., real-time audio chat) between multiple interaction clients **104**. Similarly, the video communication system **212** enables and supports video communications (e.g., real-time video chat) between multiple interaction clients **104**.

A user management system **218** is operationally responsible for the management of user data and profiles, and maintains entity information (e.g., stored in entity tables **308**, entity graphs **310**, and profile data **302**) regarding users and relationships between users of the interaction system **100**.

A collection management system **220** is operationally responsible for managing sets or collections of media (e.g., collections of text, image video, and audio data). A collection of content (e.g., messages, including images, video, text, and audio) may be organized into an "event gallery" or an "event story." Such a collection may be made available for a specified time period, such as the duration of an event to which the content relates. For example, content relating to a music concert may be made available as a "story" for the duration of that music concert. The collection management system **220** may also be responsible for publishing an icon that provides notification of a particular collection to the user interface of the interaction client **104**. The collection management system **220** includes a curation function that allows a collection manager to manage and curate a particular collection of content. For example, the curation interface enables an event organizer to curate a collection of content relating to a specific event (e.g., to delete inappropriate content or redundant messages). Additionally, the collection management system **220** employs machine vision (or image recognition technology) and content rules to curate a content collection automatically. In certain examples, compensation may be paid to a user to include user-generated content into a collection. In such cases, the collection management system **220** operates to automatically make payments to such users to use their content.

A map system **222** provides various geographic location (e.g., geolocation) functions and supports the presentation of map-based media content and messages by the interaction client **104**. For example, the map system **222** enables the display of user icons or avatars (e.g., stored in profile data **302** of FIG. **3**) on a map to indicate a current or past location of "friends" of a user, as well as media content (e.g., collections of messages including photographs and videos) generated by such friends, within the context of a map. For example, a message posted by a user to the interaction system **100** from a specific geographic location may be displayed within the context of a map at that particular location to "friends" of a specific user on a map interface of the interaction client **104**. A user can furthermore share his or her location and status information (e.g., using an appropriate status avatar) with other users of the interaction system **100** via the interaction client **104**, with this location and status information being similarly displayed within the context of a map interface of the interaction client **104** to selected users.

A game system **224** provides various gaming functions within the context of the interaction client **104**. The interaction client **104** provides a game interface providing a list of available games that can be launched by a user within the context of the interaction client **104** and played with other users of the interaction system **100**. The interaction system **100** further enables a particular user to invite other users to participate in the play of a specific game by issuing invitations to such other users from the interaction client **104**. The interaction client **104** also supports audio, video, and text messaging (e.g., chats) within the context of gameplay, provides a leaderboard for the games, and also supports the provision of in-game rewards (e.g., coins and items).

An external resource system **226** provides an interface for the interaction client **104** to communicate with remote servers (e.g., third-party servers **112**) to launch or access external resources, i.e., applications or applets. Each third-party server **112** hosts, for example, a markup language (e.g., HTML5) based application or a small-scale version of an application (e.g., game, utility, payment, or ride-sharing application). The interaction client **104** may launch a web-based resource (e.g., application) by accessing the HTML5 file from the third-party servers **112** associated with the web-based resource. Applications hosted by third-party servers **112** are programmed in JavaScript leveraging a Software Development Kit (SDK) provided by the interaction servers **124**. The SDK includes APIs with functions that can be called or invoked by the web-based application. The interaction servers **124** host a JavaScript library that provides a given external resource access to specific user data of the interaction client **104**. HTML5 is an example of technology for programming games, but applications and resources programmed based on other technologies can be used.

To integrate the functions of the SDK into the web-based resource, the SDK is downloaded by the third-party server **112** from the interaction servers **124** or is otherwise received by the third-party server **112**. Once downloaded or received, the SDK is included as part of the application code of a web-based external resource. The code of the web-based resource can then call or invoke certain functions of the SDK to integrate features of the interaction client **104** into the web-based resource.

The SDK stored on the interaction server system **110** effectively provides the bridge between an external resource (e.g., applications **106** or applets) and the interaction client **104**. This gives the user a seamless experience of communicating with other users on the interaction client **104** while also preserving the look and feel of the interaction client **104**. To bridge communications between an external resource and an interaction client **104**, the SDK facilitates communication between third-party servers **112** and the interaction client **104**. A bridge script running on a user system **102** establishes two one-way communication channels between an external resource and the interaction client **104**. Messages are sent between the external resource and the interaction client **104** via these communication channels asynchronously. Each SDK function invocation is sent as a message and callback. Each SDK function is implemented by constructing a unique callback identifier and sending a message with that callback identifier.

By using the SDK, not all information from the interaction client **104** is shared with third-party servers **112**. The SDK limits which information is shared based on the needs of the external resource. Each third-party server **112** provides an HTML5 file corresponding to the web-based external resource to interaction servers **124**. The interaction servers **124** can add a visual representation (such as a box art or other graphic) of the web-based external resource in the interaction client **104**. Once the user selects the visual representation or instructs the interaction client **104** through a graphical user interface (GUI) of the interaction client **104** to access features of the web-based external resource, the interaction client **104** obtains the HTML5 file and instantiates the resources to access the features of the web-based external resource.

The interaction client **104** presents a GUI (e.g., a landing page or title screen) for an external resource. During, before, or after presenting the landing page or title screen, the interaction client **104** determines whether the launched external resource has been previously authorized to access user data of the interaction client **104**. In response to determining that the launched external resource has been previously authorized to access user data of the interaction client **104**, the interaction client **104** presents another GUI of the external resource that includes functions and features of the external resource. In response to determining that the launched external resource has not been previously authorized to access user data of the interaction client **104**, after a threshold period of time (e.g., 3 seconds) of displaying the landing page or title screen of the external resource, the interaction client **104** slides up (e.g., animates a menu as surfacing from a bottom of the screen to a middle or other portion of the screen) a menu for authorizing the external resource to access the user data. The menu identifies the type of user data that the external resource will be authorized to use. In response to receiving a user selection of an accept option, the interaction client **104** adds the external resource to a list of authorized external resources and allows the external resource to access user data from the interaction client **104**. The external resource is authorized by the interaction client **104** to access the user data under an OAuth 2 framework.

The interaction client **104** controls the type of user data that is shared with external resources based on the type of external resource being authorized. For example, external resources that include full-scale applications (e.g., an application **106**) are provided with access to a first type of user data (e.g., 2D avatars of users with or without different avatar characteristics). As another example, external resources that include small-scale versions of applications (e.g., web-based versions of applications) are provided with access to a second type of user data (e.g., payment information, 2D avatars of users, 3D avatars of users, and avatars with various avatar characteristics). Avatar characteristics include different ways to customize a look and feel of an avatar, such as different poses, facial features, clothing, and so forth.

An advertisement system **228** operationally enables the purchasing of advertisements by third parties for presentation to end-users via the interaction clients **104** and also handles the delivery and presentation of these advertisements.

An artificial intelligence and machine learning system **230** provides a variety of services to different subsystems within the interaction system **100**. For example, the artificial intelligence and machine learning system **230** operates with the image processing system **202** and the camera system **204** to analyze images and extract information such as objects, text, or faces. This information can then be used by the image processing system **202** to enhance, filter, or manipulate images. The artificial intelligence and machine learning system **230** may be used by the augmentation system **206** to generate augmented content, XR experiences, and AR experiences, such as adding virtual objects or animations to real-world images. The communication system **208** and messaging system **210** may use the artificial intelligence and machine learning system **230** to analyze communication patterns and provide insights into how users interact with each other and provide intelligent message classification and tagging, such as categorizing messages based on sentiment or topic. The artificial intelligence and machine learning system **230** may also provide chatbot functionality to message interactions **120** between user systems **102** and between a user system **102** and the interaction server system **110**. The

artificial intelligence and machine learning system **230** may also work with the audio communication system **216** to provide speech recognition and natural language processing capabilities, allowing users to interact with the interaction system **100** using voice commands. In some cases, the artificial intelligence and machine learning system **230** can implement one or more machine learning models that generate a 3D mesh of an object depicted in a 2D image using a combination of a head-specific canonical reconstruction network and/or a body canonical reconstruction network.

## Data Architecture

FIG. **3** is a schematic diagram illustrating data structures **300**, which may be stored in a database **304** of the interaction server system **110**, according to certain examples. While the content of the database **304** is shown to comprise multiple tables, it will be appreciated that the data could be stored in other types of data structures (e.g., as an object-oriented database).

The database **304** includes message data stored within a message table **306**. This message data includes, for any particular message, at least message sender data, message recipient (or receiver) data, and a payload. Further details regarding information that may be included in a message, and included within the message data stored in the message table **306**, are described below with reference to FIG. **4**.

An entity table **308** stores entity data, and is linked (e.g., referentially) to an entity graph **310** and profile data **302**. Entities for which records are maintained within the entity table **308** may include individuals, corporate entities, organizations, objects, places, events, and so forth. Regardless of entity type, any entity regarding which the interaction server system **110** stores data may be a recognized entity. Each entity is provided with a unique identifier, as well as an entity type identifier (not shown).

The entity graph **310** stores information regarding relationships and associations between entities. Such relationships may be social, professional (e.g., work at a common corporation or organization), interest-based, or activity-based, merely for example. Certain relationships between entities may be unidirectional, such as a subscription by an individual user to digital content of a commercial or publishing user (e.g., a newspaper or other digital media outlet, or a brand). Other relationships may be bidirectional, such as a “friend” relationship between individual users of the interaction system **100**.

Certain permissions and relationships may be attached to each relationship, and also to each direction of a relationship. For example, a bidirectional relationship (e.g., a friend relationship between individual users) may include authorization for the publication of digital content items between the individual users, but may impose certain restrictions or filters on the publication of such digital content items (e.g., based on content characteristics, location data or time of day data). Similarly, a subscription relationship between an individual user and a commercial user may impose different degrees of restrictions on the publication of digital content from the commercial user to the individual user, and may significantly restrict or block the publication of digital content from the individual user to the commercial user. A particular user, as an example of an entity, may record certain restrictions (e.g., by way of privacy settings) in a record for that entity within the entity table **308**. Such privacy settings may be applied to all types of relationships within the context of the interaction system **100** or may selectively be applied to certain types of relationships.

The profile data **302** stores multiple types of profile data about a particular entity. The profile data **302** may be selectively used and presented to other users of the interaction system **100** based on privacy settings specified by a particular entity. Where the entity is an individual, the profile data **302** includes, for example, a username, telephone number, address, settings (e.g., notification and privacy settings), and a user-selected avatar representation (or collection of such avatar representations). A particular user may then selectively include one or more of these avatar representations within the content of messages communicated via the interaction system **100** and on map interfaces displayed by interaction clients **104** to other users. The collection of avatar representations may include "status avatars," which present a graphical representation of a status or activity that the user may select to communicate at a particular time.

Where the entity is a group, the profile data **302** for the group may similarly include one or more avatar representations associated with the group, in addition to the group name, members, and various settings (e.g., notifications) for the relevant group.

The database **304** also stores augmentation data, such as overlays or filters, in an augmentation table **312**. The augmentation data is associated with and applied to videos (for which data is stored in a video table **314**) and images (for which data is stored in an image table **316**).

Filters, in some examples, are overlays that are displayed as overlaid on an image or video during presentation to a recipient user. Filters may be of various types, including user-selected filters from a set of filters presented to a sending user by the interaction client **104** when the sending user is composing a message. Other types of filters include geolocation filters (also known as geo-filters), which may be presented to a sending user based on geographic location. For example, geolocation filters specific to a neighborhood or special location may be presented within a user interface by the interaction client **104**, based on geolocation information determined by a Global Positioning System (GPS) unit of the user system **102**.

Another type of filter is a data filter, which may be selectively presented to a sending user by the interaction client **104** based on other inputs or information gathered by the user system **102** during the message creation process. Examples of data filters include current temperature at a specific location, a current speed at which a sending user is traveling, battery life for a user system **102**, or the current time.

Other augmentation data that may be stored within the image table **316** includes AR content items (e.g., corresponding to applying "lenses" or AR experiences). An AR content item may be a real-time special effect and sound that may be added to an image or a video.

A collections table **318** stores data regarding collections of messages and associated image, video, or audio data, which are compiled into a collection (e.g., a story or a gallery). The creation of a particular collection may be initiated by a particular user (e.g., each user for which a record is maintained in the entity table **308**). A user may create a "personal story" in the form of a collection of content that has been created and sent/broadcast by that user. To this end, the user interface of the interaction client **104** may include an icon that is user-selectable to enable a sending user to add specific content to his or her personal story.

A collection may also constitute a "live story," which is a collection of content from multiple users that is created manually, automatically, or using a combination of manual and automatic techniques. For example, a "live story" may constitute a curated stream of user-submitted content from various locations and events. Users whose client devices have location services enabled and are at a common location event at a particular time may, for example, be presented with an option, via a user interface of the interaction client **104**, to contribute content to a particular live story. The live story may be identified to the user by the interaction client **104**, based on his or her location. The end result is a "live story" told from a community perspective.

A further type of content collection is known as a "location story," which enables a user whose user system **102** is located within a specific geographic location (e.g., on a college or university campus) to contribute to a particular collection. In some examples, a contribution to a location story may employ a second degree of authentication to verify that the end-user belongs to a specific organization or other entity (e.g., is a student on the university campus).

As mentioned above, the video table **314** stores video data that, in some examples, is associated with messages for which records are maintained within the message table **306**. Similarly, the image table **316** stores image data associated with messages for which message data is stored in the entity table **308**. The entity table **308** may associate various augmentations from the augmentation table **312** with various images and videos stored in the image table **316** and the video table **314**.

The databases **304** also include trained machine learning techniques **307** that stores parameters of one or more machine learning models that have been trained during training of the mesh generation system **500**. For example, trained machine learning techniques **307** stores the trained parameters of one or more artificial neural network machine learning models or techniques.

## Data Communications Architecture

FIG. **4** is a schematic diagram illustrating a structure of a message **400**, according to some examples, generated by an interaction client **104** for communication to a further interaction client **104** via the interaction servers **124**. The content of a particular message **400** is used to populate the message table **306** stored within the database **304**, accessible by the interaction servers **124**. Similarly, the content of a message **400** is stored in memory as "in-transit" or "in-flight" data of the user system **102** or the interaction servers **124**. A message **400** is shown to include the following example components:

- Message identifier **402**: a unique identifier that identifies the message **400**.
- Message text payload **404**: text, to be generated by a user via a user interface of the user system **102**, and that is included in the message **400**.
- Message image payload **406**: image data, captured by a camera component of a user system **102** or retrieved from a memory component of a user system **102**, and that is included in the message **400**. Image data for a sent or received message **400** may be stored in the image table **316**.
- Message video payload **408**: video data, captured by a camera component or retrieved from a memory component of the user system **102**, and that is included in the message **400**. Video data for a sent or received message **400** may be stored in the image table **316**.

- Message audio payload **410**: audio data, captured by a microphone or retrieved from a memory component of the user system **102**, and that is included in the message **400**.
- Message augmentation data **412**: augmentation data (e.g., filters, stickers, or other annotations or enhancements) that represents augmentations to be applied to message image payload **406**, message video payload **408**, or message audio payload **410** of the message **400**. Augmentation data for a sent or received message **400** may be stored in the augmentation table **312**.
- Message duration parameter **414**: parameter value indicating, in seconds, the amount of time for which content of the message (e.g., the message image payload **406**, message video payload **408**, message audio payload **410**) is to be presented or made accessible to a user via the interaction client **104**.
- Message geolocation parameter **416**: geolocation data (e.g., latitudinal and longitudinal coordinates) associated with the content payload of the message. Multiple message geolocation parameter **416** values may be included in the payload, each of these parameter values being associated with respect to content items included in the content (e.g., a specific image within the message image payload **406**, or a specific video in the message video payload **408**).
- Message story identifier **418**: identifier values identifying one or more content collections (e.g., "stories" identified in the collections table **318**) with which a particular content item in the message image payload **406** of the message **400** is associated. For example, multiple images within the message image payload **406** may each be associated with multiple content collections using identifier values.
- Message tag **420**: each message **400** may be tagged with multiple tags, each of which is indicative of the subject matter of content included in the message payload. For example, where a particular image included in the message image payload **406** depicts an animal (e.g., a lion), a tag value may be included within the message tag **420** that is indicative of the relevant animal. Tag values may be generated manually, based on user input, or may be automatically generated using, for example, image recognition.
- Message sender identifier **422**: an identifier (e.g., a messaging system identifier, email address, or device identifier) indicative of a user of the user system **102** on which the message **400** was generated and from which the message **400** was sent.
- Message receiver identifier **424**: an identifier (e.g., a messaging system identifier, email address, or device identifier) indicative of a user of the user system **102** to which the message **400** is addressed.

The contents (e.g., values) of the various components of message **400** may be pointers to locations in tables within which content data values are stored. For example, an image value in the message image payload **406** may be a pointer to (or address of) a location within an image table **316**. Similarly, values within the message video payload **408** may point to data stored within an image table **316**, values stored within the message augmentation data **412** may point to data stored in an augmentation table **312**, values stored within the message story identifier **418** may point to data stored in a collections table **318**, and values stored within the message sender identifier **422** and the message receiver identifier **424** may point to user records stored within an entity table **308**.

## Mesh Generation System

FIG. **5** is a block diagram showing an example mesh generation system **500**, according to some examples. The mesh generation system **500** receives a 2D image that depicts an object, such as a human person, and generates a 3D mesh representing the object using a combination of multiple machine learning models. Particularly, the mesh generation system **500** uses a first machine learning model to predict a volumetric reconstruction tensor and a pose output representing a pose of the object depicted in the image simultaneously or together. The mesh generation system **500** accesses a canonical body reconstruction (e.g., a canonical pose) in the canonical space and identifies a pixel or point in the volumetric reconstruction tensor that corresponds to a particular point in the canonical pose using the pose output. The mesh generation system **500** then classifies the identified pixel or point as being inside or outside of the canonical pose. After iterating through every single point in the canonical pose in this manner, the mesh generation system **500** classifies all of the points in the volumetric reconstruction tensor as being inside or outside of the canonical pose. The points that are determined to be inside the canonical pose are then used to generate a 3D mesh which can be animated to provide one or more XR experiences.

In some examples, the mesh generation system **500** accesses a monocular image depicting an object. The mesh generation system **500** predicts both a volumetric reconstruction tensor of the monocular image and a pose of the object by applying a first machine learning model to the monocular image. The mesh generation system **500** identifies a portion of the pose of the object that corresponds to a point in a canonical space associated with a set of position encoding information. The mesh generation system **500** obtains a point of the volumetric reconstruction tensor corresponding to the identified portion of the pose. The mesh generation system **500** classifies the obtained point as being inside or outside of a canonical volume by applying a second machine learning model to the obtained point of the volumetric reconstruction tensor together with the set of position encoding information. The mesh generation system **500** generates a 3D mesh representing the object in the canonical space in response to classifying the obtained point as being inside or outside of the canonical volume.

In some examples, the pose of the object includes a skeletal representation of the object. In some examples, the mesh generation system **500** selects the point in the canonical space associated with the set of position encoding information. In some examples, the mesh generation system **500** selects a second portion of the pose of the object that corresponds to a second point in the canonical space associated with a second set of position encoding information. The mesh generation system **500** obtains a second point of the volumetric reconstruction tensor corresponding to the second portion of the pose. The mesh generation system **500** classifies the second point as being inside or outside of the canonical volume by applying the second machine learning model to the second point of the volumetric reconstruction tensor together with the second set of position encoding information.

In some examples, the mesh generation system **500** repeats selection of portions of the pose and classification of points of the volumetric reconstruction tensor corresponding to the selected portions of the pose as being inside or outside of the canonical volume for each portion of the canonical volume. In some examples, the set of position encoding information represents different body parts of the canonical volume, such as arms, legs, torso, head, hands, feet, and so forth.

In some examples, the mesh generation system **500** trains the first and second machine learning models by performing training operations. These training operations include obtaining a set of training images depicting objects. Each of the set of training images is associated with 3D scans of the objects depicted in the set of training images and generate ground truth canonical space representations of the objects depicted in the set of training images by modifying poses of the 3D scans of the objects to correspond to a pose in the canonical space.

In some examples, the training operations include selecting a first training image depicting a first object corresponding to a first of the ground truth canonical space representations of the first object. The training operations include predicting both an individual volumetric reconstruction tensor of the monocular image and an individual pose of the first object by applying the first machine learning model to the first training image. The training operations include identifying an individual portion of the individual pose of the first object that corresponds to an individual point in the canonical space associated with an individual set of position encoding information. The training operations include obtaining an individual point of the individual volumetric reconstruction tensor corresponding to the individual portion. The training operations include classifying the individual point as being inside or outside of an individual canonical volume by applying the second machine learning model to the individual point of the volumetric reconstruction tensor together with the individual set of position encoding information. The training operations include generating occupancy loss based on a deviation between a classification resulting from classifying the individual point and a corresponding portion of the first ground truth canonical space representation of the object. In some examples, the mesh generation system **500** updates one or more parameters of the first and second machine learning models based on the occupancy loss.

In some examples, the training operations include generating an individual 3D mesh representing the first object in the canonical space in response to classifying the individual point as being inside or outside of the canonical volume. The training operations include posing the individual 3D mesh based on the individual pose of the first object predicted by the first machine learning model and computing a posed loss based on a deviation between the posed individual 3D mesh and the 3D scan of the first object. In some examples, the mesh generation system **500** updates one or more parameters of the first and second machine learning models based on the posed loss.

In some examples, the mesh generation system **500** crops a portion of the monocular image corresponding to a head of the object and generates, based on the cropped portion of the monocular image, facial landmarks of the head of the object. The mesh generation system **500** predicts a head-specific canonical space reconstruction by applying a head-specific canonical network to the cropped portion based on the generated facial landmarks. The mesh generation system **500** combines the head-specific canonical space reconstruction with the canonical volume corresponding to the object.

In some examples, the mesh generation system **500** selects a facial landmark in a head-specific canonical space representation of the object. The mesh generation system **500** identifies a specific portion of the object depicted in the cropped portion of the monocular image that corresponds to the selected facial landmark. The mesh generation system **500** obtains an individual point of the volumetric reconstruction tensor corresponding to the specific portion and classifies the obtained individual point as being inside or outside of the head-specific canonical space representation of the object by applying a third machine learning model to the obtained individual point. The mesh generation system **500** generates the head-specific canonical space reconstruction in response to classifying the obtained individual point as being inside or outside of the head-specific canonical space representation.

In some examples, the mesh generation system **500** predicts both an additional volumetric reconstruction tensor of the cropped portion of the monocular image and a head pose of the object by applying a fourth machine learning model to the cropped portion of the monocular image. The individual point can be obtained from the additional volumetric reconstruction tensor. In some examples, the mesh generation system **500** updates a pose of a head region in the canonical volume based on the facial landmarks. The 3D mesh is generated using the canonical volume with the updated pose of the head region.

In some examples, the canonical volume represents a full body canonical space reconstruction of the object. The mesh generation system **500** identifies a region in which the full body canonical space reconstruction of the object overlaps with the head-specific canonical space reconstruction. The mesh generation system **500** smoothly deforms (e.g., by integrating values of) the region based on differences between the full body canonical space reconstruction of the object and the head-specific canonical space reconstruction. In some examples, the mesh generation system **500** generates the 3D mesh based on the full body canonical space reconstruction, the head-specific canonical space reconstruction, and/or the smoothly deformed region.

In some examples, the mesh generation system **500** generates an XR object based on the 3D mesh. In some examples, the mesh generation system **500** animates the XR object in an XR view of a real-world environment captured in real time by a camera of the user system **102**.

For example, the mesh generation system **500** includes an image access component **510**. The image access component **510** can access a real-time or previously stored image or video from the user system **102**. The image access component **510** can select a frame or collection of frames from the accessed image or video for use in generating a 3D mesh of one or more real-world or XR objects depicted in the selected frame or collection of frames. During training of the mesh generation system **500**, the image access component **510** accesses a database of training data to retrieve images depicting real-world objects and their corresponding ground truth 3D scans to train one or more machine learning models of the mesh generation system **500**.

During operation (e.g., after being trained), the image access component **510** provides the image depicting the object simultaneously or sequentially to a body canonical reconstruction network **520** and/or to a head-specific canonical reconstruction network **530**. The body canonical reconstruction network **520** includes a first plurality of machine learning models (e.g., first and second machine learning models) that are trained to process a received image and generate a canonical representation of the object depicted in the received image. The operations performed by the body canonical reconstruction network **520** are described in more detail in connection with FIG. **6** below. The head-specific canonical reconstruction network **530** includes a second plurality of machine learning models (e.g., third and fourth machine learning models) that are trained to process a received image, crop a portion of the image corresponding to a head, such as based on an output of the first and/or second machine learning models, and generate a head-specific canonical representation of only the head portion of the object depicted in the received image. In this way, the body canonical reconstruction network **520** provides or generates a generic and general body representation of the object depicted in the image in canonical space and the head-specific canonical reconstruction network **530** generates a head-specific representation of the facial features and head of the object depicted in the image, which includes a very detailed representation of the head and face of the object.

The outputs of the head-specific canonical reconstruction network **530** and the body canonical reconstruction network **520** are provided to a mesh generation component **540**. The mesh generation component **540** combines a body portion of the body representation of the object (e.g., excluding the head) with the head portion of the head-specific representation of the object (e.g., excluding a neck which may be included in the output of the head-specific canonical reconstruction network **530**). The mesh generation component **540** can identify a region of the body representation that overlaps a region of the head-specific representation. For example, the mesh generation component **540** can determine that a neck in the head-specific representation is also included in the body representation. This overlap region can be interpolated or smoothed to smooth out or interpolate any differences between the overlapping regions. The mesh generation component **540** then includes this smoothed region in the combined reconstruction of the object formed by the body representation and head-specific representation to form a final representation of the object depicted in the image. The mesh generation component **540** generates a 3D mesh using the final representation of the object and applies the 3D mesh to a character or avatar depicted in an image to provide an XR experience. The mesh generation component **540** animates the character or avatar based on movement of the person depicted in the image.

FIG. **6** is a diagrammatic representation of a full body canonical space reconstruction system **600**, in accordance with some examples. Specifically, the full body canonical space reconstruction system **600** can implement some or all of the components of the body canonical reconstruction network **520**. The full body canonical space reconstruction system **600** includes an image **601** that can be received from the image access component **510**. The image **601** can depict an object, such as a person and a background. The full body canonical space reconstruction system **600** includes a first machine learning model **610**. The first machine learning model **610** processes the image **601** and simultaneously outputs both a volumetric reconstruction tensor **612** and a pose output **614**. The volumetric reconstruction tensor **612** is a tensor of estimated pixel values of each point of the image **601**. In some cases, the volumetric reconstruction tensor **612** provides estimated pixel values of 3D or estimated 3D points of various portions of the image **601**. The volumetric reconstruction tensor **612** can be a mathematical representation of a 3D scene or object using a four-dimensional (4D) tensor, which is a multidimensional array of numbers. This tensor can capture the spatial and angular information of the scene or object, such as its shape, color, and lighting.

The pose output **614** includes a skeleton with various bones arranged to represent a current pose of the object depicted in the image **601**. The bones of the skeleton included in the pose output **614** can be arranged to mimic a look of the skeletal features of the object, such as the person, depicted in the image **601**. In some examples, the full body canonical space reconstruction system **600** accesses a canonical pose **640** representing a pose of an object in the canonical space. In some cases, the canonical pose **640** can correspond to a T-pose of an object, where the arms are stretched out extending as far away from the body of the object as possible and the legs are also stretched open. The canonical pose **640** can differ from the pose output **614**. In some cases, the canonical pose can be any other type of pose and is not limited to a T-pose.

The full body canonical space reconstruction system **600** selects a particular portion of the canonical pose **640**, such as a torso or hand portion of the canonical pose **640**. The full body canonical space reconstruction system **600** identifies a set of positional encoding information corresponding to the selected particular portion. The set of positional encoding information can specify the collection of points and their locations for the particular portion. Namely, a first set of positional encoding information can identify or specify locations of points on the canonical pose **640** corresponding to a first body part, such as torso. A second set of positional encoding information can identify or specify locations of points on the canonical pose **640** corresponding to a second body part, such as legs.

The full body canonical space reconstruction system **600** can select a particular point from the particular portion of the canonical pose **640**. The full body canonical space reconstruction system **600** can then access the pose output **614** to identify the portion of the pose output **614** that corresponds to the particular portion of the canonical pose **640** that was selected. For example, if a torso was selected from the canonical pose **640**, the full body canonical space reconstruction system **600** can identify the torso region of the pose output **614**. The full body canonical space reconstruction system **600** can select or identify a point within the pose output **614** that corresponds to the selected point of the particular portion of the canonical pose **640**.

The full body canonical space reconstruction system **600** uses the selected point of the pose output **614** to retrieve a point or set of points from the volumetric reconstruction tensor **612** that match the selected point of the pose output **614**. In some cases, the full body canonical space reconstruction system **600** repeats the above process for each point and for each portion of the canonical pose **640** to form a signal **620** that includes an image-aligned tensor and position encoding values corresponding to each selected particular portion of the canonical pose **640**. For example, the full body canonical space reconstruction system **600** can select a collection of points from a second portion of the canonical pose **640** associated with a second set of positional encoding information. The full body canonical space reconstruction system **600** can identify which portion of the pose output **614** corresponds to the second portion of the canonical pose **640** and use that portion to retrieve the pixel values from the volumetric reconstruction tensor **612**. The retrieved pixel values are then stored in the signal **620** in association with the second set of positional encoding information. After all of the portions of the canonical pose **640** are processed in this manner to identify, retrieve, and associate each pixel in the volumetric reconstruction tensor **612** with the corresponding positional encoding information, the signal **620** is generated.

The full body canonical space reconstruction system **600** can then provide the signal **620** that includes an image-aligned tensor and position encoding values corresponding to one or more portions (or all portions) of the canonical pose **640** to a second machine learning model **630**. The second machine learning model **630** classifies each of the points in the signal **620** as being inside or outside of the canonical pose **640**. After the points of the volumetric reconstruction tensor **612** are all classified, the full body canonical space reconstruction system **600** outputs the pixel values that are classified as being inside of the canonical pose **640** to form the body representation of the object depicted in the image **601**. Namely, this body representation corresponds to the output of the body canonical reconstruction network **520**.

In some examples, the full body canonical space reconstruction system **600** is trained using training data received from the image access component **510**. The full body canonical space reconstruction system **600** can be trained using multiple types of training losses including a template loss and posed loss. FIG. **7** is a diagrammatic representation **700** of training losses for the full body canonical space reconstruction system **600**, in accordance with some examples.

As shown in FIG. **7**, to train the full body canonical space reconstruction system **600**, the full body canonical space reconstruction system **600** retrieves a first training image that depicts a person and the corresponding 3D scan of the person. The full body canonical space reconstruction system **600** generates a ground truth canonical pose representing the person using the 3D scan. The full body canonical space reconstruction system **600** then processes the first training image using the first machine learning model **610** to generate a training volumetric reconstruction tensor **612** and the corresponding pose output **614** representing the current pose of the person depicted in the first training image. The full body canonical space reconstruction system **600** selects points along the canonical pose (e.g., the ground truth canonical pose representing the person) and uses those points to retrieve corresponding collections of points from the volumetric reconstruction tensor **612** based on the pose output **614**.

Namely, the full body canonical space reconstruction system **600** forms a signal representing all of the points from the volumetric reconstruction tensor **612** that are associated with different portions of the canonical pose. To do so, the full body canonical space reconstruction system **600** can select an arm portion of the canonical pose and use the pose output **614** to determine which portion or set of pixels in the volumetric reconstruction tensor **612** correspond to the arm portion. Those pixels are then inserted into a signal and associated with the arm portion. This process is repeated for the leg portion, torso portion, and all other portions of the canonical pose until all portions are associated with position encoding information (e.g., labeled) for the corresponding pixel values of the volumetric reconstruction tensor **612**. The full body canonical space reconstruction system **600** then applies the second machine learning model **630** to the signal that includes the pixels and the associated positional encoding information to classify the pixel values as being inside or outside of the canonical space. The full body canonical space reconstruction system **600** retrieves the pixels classified as being within the canonical space and compares those values with the ground truth pixel values from the ground truth canonical space representation of the person. The full body canonical space reconstruction system **600** computes a deviation between the pixels classified as being within the canonical space and the ground truth pixel values from the ground truth canonical space representation of the person. This deviation is used to generate an occupancy loss (e.g., the template-space reconstruction loss **710**) which is used to update one or more parameters of the first machine learning model **610** and/or the second machine learning model **630**. In this way, the first machine learning model **610** that generates both the pose output **614** and the volumetric reconstruction tensor **612** is updated using the same training loss, which improves the overall accuracy and efficiency of generating these signals.

In some examples, the full body canonical space reconstruction system **600** generates a 3D training mesh using the pixels classified as being within the canonical space. The 3D training mesh is posed based on the pose output **614** of the first training image. The 3D training mesh is then compared with the 3D scan of the person depicted in the first training image to generate a posed-space reconstruction loss **720**. A deviation resulting from this comparison is used to generate a posed loss, which is used to update one or more parameters of the first machine learning model **610** and/or the second machine learning model **630**. In this way, the first machine learning model **610** that generates both the pose output **614** and the volumetric reconstruction tensor **612** is updated using this additional training loss, which improves the overall accuracy and efficiency of generating these signals.

FIG. **8** is a diagrammatic representation **800** of head pose refinement for the full body canonical space reconstruction system, in accordance with some examples. Specifically, the head-specific canonical reconstruction network **530** can process the image received from the image access component **510** to crop a region **810** of the image that corresponds to the head portion of the object depicted in the image. The head-specific canonical reconstruction network **530** can use the pose output **614** received from the signal **620** to select the portion of the image corresponding to the head and/or can use any other image recognition techniques to retrieve and identify the portion of the image corresponding to the head.

The head-specific canonical reconstruction network **530** can process the cropped region **810** of the image to identify 2D facial landmarks of the head depicted in the cropped region **810** of the image. These 2D facial landmarks can be provided to the body canonical reconstruction network **520** to update a pose of the head generated by the body canonical reconstruction network **520**. Namely, a 3D mesh can be generated using the output of the body canonical reconstruction network **520**, such as mesh **820**. The mesh **820** can then be updated, such as by refining or modifying a pose of the head portion, to generate a new mesh **830** in which the head pose is modified based on the 2D facial landmarks detected in the cropped region **810**.

In some examples, the head-specific canonical reconstruction network **530** can process the cropped region **810** in parallel with or sequentially after the body canonical reconstruction network **520** is used to generate the canonical body representation of the object depicted in the image received from the image access component **510**. The head-specific canonical reconstruction network **530** can perform a similar process as the body canonical reconstruction network **520** to generate a head-specific canonical representation of the head depicted in the cropped region **810**. For example, the head-specific canonical reconstruction network **530** can implement a third machine learning model (which can perform functions similar to the first machine learning model **610** but specific to a head portion of a person). The third machine learning model processes the cropped region **810** and simultaneously outputs both a head-specific volumetric reconstruction tensor and a head-specific pose output.

In some examples, the head-specific canonical reconstruction network **530** accesses a head-specific canonical pose representing a pose of a head of an object in the canonical space. The head-specific canonical reconstruction network **530** selects a facial feature of the head-specific canonical pose, such as eyes or a mouth portion of the head-specific canonical pose. The head-specific canonical reconstruction network **530** identifies a set of head-specific positional encoding information corresponding to the selected facial feature. The set of positional encoding information can specify the collection of points and their locations for the particular facial feature. The head-specific canonical reconstruction network **530** can then access the head-specific pose output **614** to identify the portion of the head-specific pose output **614** that corresponds to the particular facial feature of the head-specific canonical pose that was selected. The head-specific canonical reconstruction network **530** uses the selected point of the head-specific pose output to retrieve a point or set of points from the head-specific volumetric reconstruction tensor that match the selected point of the head-specific pose output. In some cases, the head-specific canonical reconstruction network **530** repeats the above process for each point and for each facial feature of the head-specific canonical pose to form a signal that includes an image-aligned head-specific tensor and position encoding values corresponding to each selected particular facial feature of the head-specific canonical pose. After all of the facial features of the head-specific canonical pose are processed in this manner to identify, retrieve, and associate each pixel in the head-specific volumetric reconstruction tensor with the corresponding positional encoding information, the head-specific signal is generated.

The head-specific canonical reconstruction network **530** can then provide the head-specific signal that includes an image-aligned head-specific tensor and position encoding values corresponding to one or more facial features (or all facial features) of the head-specific canonical pose to a fourth machine learning model. The fourth machine learning model classifies each of the points in the head-specific signal as being inside or outside of the head-specific canonical pose. After the points of the head-specific volumetric reconstruction tensor are all classified, the head-specific canonical reconstruction network **530** outputs the pixel values that are classified as being inside of the head-specific canonical pose to form the head-specific representation of the object depicted in the image.

In some examples, the head-specific canonical space reconstruction system is trained using the same or different training data as that used to train the full body canonical space reconstruction system **600**. To train the head-specific canonical space reconstruction system, the head-specific canonical space reconstruction system retrieves a first training image that depicts a head of a person and the corresponding 3D scan of the person. The head-specific canonical space reconstruction system generates a ground truth canonical head-specific pose representing the head of the person using the 3D scan. The head-specific canonical space reconstruction system then processes the first training image using the third machine learning model to generate a training head-specific volumetric reconstruction tensor and the corresponding head-specific pose output representing the current head-specific pose of the person depicted in the first training image. The head-specific canonical space reconstruction system selects points along the head-specific canonical pose (e.g., the ground truth canonical pose representing the head of the person) and uses those points to retrieve corresponding collections of points from the head-specific volumetric reconstruction tensor based on the head-specific pose output **614**.

The head-specific canonical space reconstruction system then applies the fourth machine learning model to the signal that includes the pixels and the associated positional encoding information specific to the head to classify the pixel values as being inside or outside of the head-specific canonical space. The head-specific canonical space reconstruction system retrieves the pixels classified as being within the head-specific canonical space and compares those values with the ground truth pixel values from the ground truth head-specific canonical space representation of the person. The head-specific canonical space reconstruction system computes a deviation between the pixels classified as being within the head-specific canonical space and the ground truth pixel values from the ground truth head-specific canonical space representation of the person. This deviation is used to generate a head-specific occupancy loss which is used to update one or more parameters of the third machine learning model and/or the fourth machine learning model.

FIG. **9** is a diagrammatic representation **900** of a mesh generation component of the full body canonical space reconstruction system, in accordance with some examples. Specifically, as shown in FIG. **9**, the input image **601** can be processed by the body canonical reconstruction network **520** and the head-specific canonical reconstruction network **530** to generate a head-specific canonical representation **910** of the object depicted in the image **601** and a full body canonical representation **920** of the object depicted in the image **601**. The mesh generation system **500** can use the head portion of the head-specific canonical representation **910** and the body portion of the full body canonical representation **920** to generate a final reconstruction **930** of the object depicted in the image **601**. In particular, the mesh generation system **500** can select a threshold region of the head-specific canonical representation **910** (e.g., a top of a person's neck) which is used to cut off the portions of the head-specific canonical representation **910** used to form the final reconstruction **930**. Similarly, the mesh generation system **500** can select another threshold region of the full body canonical representation **920** (e.g., a bottom of the person's neck) which is used to cut off the portions of the full body canonical representation **920** used to form the final reconstruction **930**. The mesh generation system **500** can determine that a region **912** of the head-specific canonical representation **910** overlaps with a region **922** of the full body canonical representation **920**. Namely, both the head-specific canonical representation **910** and the full body canonical representation **920** can include a neck region. The mesh generation system **500** can interpolate differences between the overlapping portions to smooth out the pixel values and use those smoothed pixel values to generate the final reconstruction **930**. The final reconstruction **930** can then be used to form a 3D mesh of the object depicted in the image **601**.

FIG. **10** is a flowchart of a process **1000** performed by the mesh generation system **500**, in accordance with some examples. Although the flowchart can describe the operations as a sequential process, many of the operations can be performed in parallel or concurrently. In addition, the order of the operations may be re-arranged. A process is terminated when its operations are completed. A process may correspond to a method, a procedure, and the like. The steps of methods may be performed in whole or in part, may be performed in conjunction with some or all of the steps in other methods, and may be performed by any number of different systems or any portion thereof, such as a processor included in any of the systems.

At operation **1001**, the mesh generation system **500** (e.g., a user system **102** or a server) accesses a monocular image depicting an object, as discussed above.

At operation **1002**, the mesh generation system **500** predicts both a volumetric reconstruction tensor of the monocular image and a pose of the object by applying a first machine learning model to the monocular image, as discussed above.

At operation **1003**, the mesh generation system **500** identifies a portion of the pose of the object that corresponds to a point in a canonical space associated with a set of position encoding information, as discussed above.

At operation **1004**, the mesh generation system **500** obtains a point of the volumetric reconstruction tensor corresponding to the identified portion of the pose, as discussed above.

At operation **1005**, the mesh generation system **500** classifies the obtained point as being inside or outside of a canonical volume by applying a second machine learning model to the obtained point of the volumetric reconstruction tensor together with the set of position encoding information, as discussed above.

At operation **1006**, the mesh generation system **500** generates a 3D mesh representing the object in the canonical space in response to classifying the obtained point as being inside or outside of the canonical volume, as discussed above.

## EXAMPLES

### Example 1

A method comprising: accessing a monocular image depicting an object; predicting both a volumetric reconstruction tensor of the monocular image and a pose of the object by applying a first machine learning model to the monocular image; identifying a portion of the pose of the object that corresponds to a point in a canonical space associated with a set of position encoding information; obtaining a point of the volumetric reconstruction tensor corresponding to the identified portion of the pose; classifying the obtained point as being inside or outside of a canonical volume by applying a second machine learning model to the obtained point of the volumetric reconstruction tensor together with the set of position encoding information; and generating a 3D mesh representing the object in the canonical space in response to classifying the obtained point as being inside or outside of the canonical volume.

### Example 2

The method of Example 1, wherein the pose of the object comprises a skeletal representation of the object.

### Example 3

The method of any one of Examples 1-2, further comprising: selecting the point in the canonical space associated with the set of position encoding information.

### Example 4

The method of any one of Examples 1-3, further comprising: selecting a second portion of the pose of the object

that corresponds to a second point in the canonical space associated with a second set of position encoding information; obtaining a second point of the volumetric reconstruction tensor corresponding to the second portion of the pose; and classifying the second point as being inside or outside of the canonical volume by applying the second machine learning model to the second point of the volumetric reconstruction tensor together with the second set of position encoding information.

### Example 5

The method of Example 4, further comprising repeating selection of portions of the pose and classification of points of the volumetric reconstruction tensor corresponding to the selected portions of the pose as being inside or outside of the canonical volume for each portion of the canonical volume.

### Example 6

The method of any one of Examples 1-5, wherein the set of position encoding information represents different body parts of the canonical volume.

### Example 7

The method of any one of Examples 1-6, further comprising training the first and second machine learning models by performing training operations comprising: obtaining a set of training images depicting objects, each of the set of training images being associated with 3D scans of the objects depicted in the set of training images; and generating ground truth canonical space representations of the objects depicted in the set of training images by modifying poses of the 3D scans of the objects to correspond to a pose in the canonical space.

### Example 8

The method of Example 7, wherein the training operations comprise: selecting a first training image depicting a first object corresponding to a first of the ground truth canonical space representations of the first object; predicting both an individual volumetric reconstruction tensor of the monocular image and an individual pose of the first object by applying the first machine learning model to the first training image; identifying an individual portion of the individual pose of the first object that corresponds to an individual point in the canonical space associated with an individual set of position encoding information; obtaining an individual point of the individual volumetric reconstruction tensor corresponding to the individual portion; classifying the individual point as being inside or outside of an individual canonical volume by applying the second machine learning model to the individual point of the volumetric reconstruction tensor together with the individual set of position encoding information; and generating occupancy loss based on a deviation between a classification resulting from classifying the individual point and a corresponding portion of the first ground truth canonical space representation of the object.

### Example 9

The method of Example 8, further comprising updating one or more parameters of the first and second machine learning models based on the occupancy loss.

Example 10

The method of any one of Examples 8-9, further comprising: generating an individual 3D mesh representing the first object in the canonical space in response to classifying the individual point as being inside or outside of the canonical volume; posing the individual 3D mesh based on the individual pose of the first object predicted by the first machine learning model; and computing a posed loss based on a deviation between the posed individual 3D mesh and the 3D scan of the first object.

Example 11

The method of any one of Examples 1-10, further comprising: cropping a portion of the monocular image corresponding to a head of the object; generating, based on the cropped portion of the monocular image, facial landmarks of the head of the object; predicting a head-specific canonical space reconstruction by applying a head-specific canonical network to the cropped portion based on the generated facial landmarks; and combining the head-specific canonical space reconstruction with the canonical volume corresponding to the object.

Example 12

The method of Example 11, further comprising: selecting a facial landmark in a head-specific canonical space representation of the object; identifying a specific portion of the object depicted in the cropped portion of the monocular image that corresponds to the selected facial landmark; obtaining an individual point of the volumetric reconstruction tensor corresponding to the specific portion; classifying the obtained individual point as being inside or outside of the head-specific canonical space representation of the object by applying a third machine learning model to the obtained individual point; and generating the head-specific canonical space reconstruction in response to classifying the obtained individual point as being inside or outside of the head-specific canonical space representation.

Example 13

The method of Example 12, further comprising: predicting both an additional volumetric reconstruction tensor of the cropped portion of the monocular image and a head pose of the object by applying a fourth machine learning model to the cropped portion of the monocular image, wherein the individual point is obtained from the additional volumetric reconstruction tensor.

Example 14

The method of any one of Examples 11-13, further comprising: updating a pose of a head region in the canonical volume based on the facial landmarks, wherein the 3D mesh is generated using the canonical volume with the updated pose of the head region.

Example 15

The method of any one of Examples 11-14, wherein the canonical volume represents a full body canonical space reconstruction of the object, further comprising: identifying a region in which the full body canonical space reconstruction of the object overlaps with the head-specific canonical space reconstruction; and smoothly deforming the region based on differences between the full body canonical space reconstruction of the object and the head-specific canonical space reconstruction.

Example 16

The method of Example 15, further comprising generating the 3D mesh based on the full body canonical space reconstruction, the head-specific canonical space reconstruction, and the smoothly deformed region.

Example 17

The method of any one of Examples 1-16, further comprising generating an XR object based on the 3D mesh.

Example 18

The method of Example 17, further comprising animating the XR object in a view of a real-world environment captured in real time by a camera of a user system.

Example 19

A system comprising: at least one processor; and at least one memory component having instructions stored thereon that, when executed by the at least one processor, cause the at least one processor to perform operations comprising: accessing a monocular image depicting an object; predicting both a volumetric reconstruction tensor of the monocular image and a pose of the object by applying a first machine learning model to the monocular image; identifying a portion of the pose of the object that corresponds to a point in a canonical space associated with a set of position encoding information; obtaining a point of the volumetric reconstruction tensor corresponding to the identified portion of the pose; classifying the obtained point as being inside or outside of a canonical volume by applying a second machine learning model to the obtained point of the volumetric reconstruction tensor together with the set of position encoding information; and generating a 3D mesh representing the object in the canonical space in response to classifying the obtained point as being inside or outside of the canonical volume.

Example 20

A non-transitory computer-readable storage medium having stored thereon instructions that, when executed by at least one processor, cause the at least one processor to perform operations comprising: accessing a monocular image depicting an object; predicting both a volumetric reconstruction tensor of the monocular image and a pose of the object by applying a first machine learning model to the monocular image; identifying a portion of the pose of the object that corresponds to a point in a canonical space associated with a set of position encoding information; obtaining a point of the volumetric reconstruction tensor corresponding to the identified portion of the pose; classifying the obtained point as being inside or outside of a canonical volume by applying a second machine learning model to the obtained point of the volumetric reconstruction tensor together with the set of position encoding information; and generating a 3D mesh representing the object in the canonical space in response to classifying the obtained point as being inside or outside of the canonical volume.

## Machine Architecture

FIG. **11** is a diagrammatic representation of the machine **1100** within which instructions **1102** (e.g., software, a program, an application, an applet, an app, or other executable code) for causing the machine **1100** to perform any one or more of the methodologies discussed herein may be executed. For example, the instructions **1102** may cause the machine **1100** to execute any one or more of the methods described herein. The instructions **1102** transform the general, non-programmed machine **1100** into a particular machine **1100** programmed to carry out the described and illustrated functions in the manner described. The machine **1100** may operate as a standalone device or may be coupled (e.g., networked) to other machines. In a networked deployment, the machine **1100** may operate in the capacity of a server machine or a client machine in a server-client network environment, or as a peer machine in a peer-to-peer (or distributed) network environment. The machine **1100** may comprise, but not be limited to, a server computer, a client computer, a personal computer (PC), a tablet computer, a laptop computer, a netbook, a set-top box (STB), a personal digital assistant (PDA), an entertainment media system, a cellular telephone, a smartphone, a mobile device, a wearable device (e.g., a smartwatch), a smart home device (e.g., a smart appliance), other smart devices, a web appliance, a network router, a network switch, a network bridge, or any machine capable of executing the instructions **1102**, sequentially or otherwise, that specify actions to be taken by the machine **1100**. Further, while a single machine **1100** is illustrated, the term "machine" shall also be taken to include a collection of machines that individually or jointly execute the instructions **1102** to perform any one or more of the methodologies discussed herein. The machine **1100**, for example, may comprise the user system **102** or any one of multiple server devices forming part of the interaction server system **110**. In some examples, the machine **1100** may also comprise both client and server systems, with certain operations of a particular method or algorithm being performed on the server-side and with certain operations of the particular method or algorithm being performed on the client-side.

The machine **1100** may include processors **1104**, memory **1106**, and input/output (I/O) components **1108**, which may be configured to communicate with each other via a bus **1110**. In an example, the processors **1104** (e.g., a Central Processing Unit (CPU), a Reduced Instruction Set Computing (RISC) Processor, a Complex Instruction Set Computing (CISC) Processor, a Graphics Processing Unit (GPU), a Digital Signal Processor (DSP), an Application Specific Integrated Circuit (ASIC), a Radio-Frequency Integrated Circuit (RFIC), another processor, or any suitable combination thereof) may include, for example, a processor **1112** and a processor **1114** that execute the instructions **1102**. The term "processor" is intended to include multi-core processors that may comprise two or more independent processors (sometimes referred to as "cores") that may execute instructions contemporaneously. Although FIG. **11** shows multiple processors **1104**, the machine **1100** may include a single processor with a single-core, a single processor with multiple cores (e.g., a multi-core processor), multiple processors with a single core, multiple processors with multiples cores, or any combination thereof.

The memory **1106** includes a main memory **1116**, a static memory **1118**, and a storage unit **1120**, all accessible to the processors **1104** via the bus **1110**. The main memory **1106**, the static memory **1118**, and storage unit **1120** store the instructions **1102** embodying any one or more of the methodologies or functions described herein. The instructions **1102** may also reside, completely or partially, within the main memory **1116**, within the static memory **1118**, within machine-readable medium **1122** within the storage unit **1120**, within at least one of the processors **1104** (e.g., within the processor's cache memory), or any suitable combination thereof, during execution thereof by the machine **1100**.

The I/O components **1108** may include a wide variety of components to receive input, provide output, produce output, transmit information, exchange information, capture measurements, and so on. The specific I/O components **1108** that are included in a particular machine will depend on the type of machine. For example, portable machines such as mobile phones may include a touch input device or other such input mechanisms, while a headless server machine will likely not include such a touch input device. It will be appreciated that the I/O components **1108** may include many other components that are not shown in FIG. **11**. In various examples, the I/O components **1108** may include user output components **1124** and user input components **1126**. The user output components **1124** may include visual components (e.g., a display such as a plasma display panel (PDP), a light-emitting diode (LED) display, a liquid crystal display (LCD), a projector, or a cathode ray tube (CRT)), acoustic components (e.g., speakers), haptic components (e.g., a vibratory motor, resistance mechanisms), other signal generators, and so forth. The user input components **1126** may include alphanumeric input components (e.g., a keyboard, a touch screen configured to receive alphanumeric input, a photo-optical keyboard, or other alphanumeric input components), point-based input components (e.g., a mouse, a touchpad, a trackball, a joystick, a motion sensor, or another pointing instrument), tactile input components (e.g., a physical button, a touch screen that provides location and force of touches or touch gestures, or other tactile input components), audio input components (e.g., a microphone), and the like. Any biometric collected by the biometric components is captured and stored with user approval and deleted on user request.

Further, such biometric data may be used for very limited purposes, such as identification verification. To ensure limited and authorized use of biometric information and other personally identifiable information (PII), access to this data is restricted to authorized personnel only, if allowed at all. Any use of biometric data may strictly be limited to identification verification purposes, and the data is not shared or sold to any third party without the explicit consent of the user. In addition, appropriate technical and organizational measures are implemented to ensure the security and confidentiality of this sensitive information.

In further examples, the I/O components **1108** may include biometric components **1128**, motion components **1130**, environmental components **1132**, or position components **1134**, among a wide array of other components. For example, the biometric components **1128** include components to detect expressions (e.g., hand expressions, facial expressions, vocal expressions, body gestures, or eye-tracking), measure biosignals (e.g., blood pressure, heart rate, body temperature, perspiration, or brain waves), identify a person (e.g., voice identification, retinal identification, facial identification, fingerprint identification, or electroencephalogram-based identification), and the like. The biometric components may include a brain-machine interface (BMI) system that allows communication between the brain and an external device or machine. This may be achieved by recording brain activity data, translating this data into a format that can be understood by a computer, and then using the resulting signals to control the device or machine.

Example types of BMI technologies include:

Electroencephalography (EEG) based BMIs, which record electrical activity in the brain using electrodes placed on the scalp.

Invasive BMIs, which use electrodes that are surgically implanted into the brain.

Optogenetics BMIs, which use light to control the activity of specific nerve cells in the brain.

The motion components **1130** include acceleration sensor components (e.g., accelerometer), gravitation sensor components, rotation sensor components (e.g., gyroscope).

The environmental components **1132** include, for example, one or cameras (with still image/photograph and video capabilities), illumination sensor components (e.g., photometer), temperature sensor components (e.g., one or more thermometers that detect ambient temperature), humidity sensor components, pressure sensor components (e.g., barometer), acoustic sensor components (e.g., one or more microphones that detect background noise), proximity sensor components (e.g., infrared sensors that detect nearby objects), gas sensors (e.g., gas detection sensors to detection concentrations of hazardous gases for safety or to measure pollutants in the atmosphere), or other components that may provide indications, measurements, or signals corresponding to a surrounding physical environment.

With respect to cameras, the user system **102** may have a camera system comprising, for example, front cameras on a front surface of the user system **102** and rear cameras on a rear surface of the user system **102**. The front cameras may, for example, be used to capture still images and video of a user of the user system **102** (e.g., “selfies”), which may then be augmented with augmentation data (e.g., filters) described above. The rear cameras may, for example, be used to capture still images and videos in a more traditional camera mode, with these images similarly being augmented with augmentation data. In addition to front and rear cameras, the user system **102** may also include a 360° camera for capturing 360° photographs and videos.

Further, the camera system of the user system **102** may include dual rear cameras (e.g., a primary camera as well as a depth-sensing camera), or even triple, quad, or penta rear camera configurations on the front and rear sides of the user system **102**. These multiple cameras systems may include a wide camera, an ultra-wide camera, a telephoto camera, a macro camera, and a depth sensor, for example.

The position components **1134** include location sensor components (e.g., a GPS receiver component), altitude sensor components (e.g., altimeters or barometers that detect air pressure from which altitude may be derived), orientation sensor components (e.g., magnetometers), and the like.

Communication may be implemented using a wide variety of technologies. The I/O components **1108** further include communication components **1136** operable to couple the machine **1100** to a network **1138** or devices **1140** via respective coupling or connections. For example, the communication components **1136** may include a network interface component or another suitable device to interface with the network **1138**. In further examples, the communication components **1136** may include wired communication components, wireless communication components, cellular communication components, Near Field Communication (NFC) components, Bluetooth® components (e.g., Bluetooth® Low Energy), WiFi® components, and other communication components to provide communication via other modalities. The devices **1140** may be another machine or any of a wide variety of peripheral devices (e.g., a peripheral device coupled via a universal serial bus (USB)).

Moreover, the communication components **1136** may detect identifiers or include components operable to detect identifiers. For example, the communication components **1136** may include Radio Frequency Identification (RFID) tag reader components, NFC smart tag detection components, optical reader components (e.g., an optical sensor to detect one-dimensional bar codes such as Universal Product Code (UPC) bar code, multi-dimensional bar codes such as Quick Response (QR) code, Aztec code, Data Matrix, Dataglyph™, MaxiCode, PDF417, Ultra Code, UCC RSS-2D bar code, and other optical codes), or acoustic detection components (e.g., microphones to identify tagged audio signals). In addition, a variety of information may be derived via the communication components **1136**, such as location via Internet Protocol (IP) geolocation, location via Wi-Fi® signal triangulation, location via detecting an NFC beacon signal that may indicate a particular location, and so forth.

The various memories (e.g., main memory **1116**, static memory **1118**, and memory of the processors **1104**) and storage unit **1120** may store one or more sets of instructions and data structures (e.g., software) embodying or used by any one or more of the methodologies or functions described herein. These instructions (e.g., the instructions **1102**), when executed by processors **1104**, cause various operations to implement the disclosed examples.

The instructions **1102** may be transmitted or received over the network **1138**, using a transmission medium, via a network interface device (e.g., a network interface component included in the communication components **1136**) and using any one of several well-known transfer protocols (e.g., HTTP). Similarly, the instructions **1102** may be transmitted or received using a transmission medium via a coupling (e.g., a peer-to-peer coupling) to the devices **1140**.

## Software Architecture

FIG. **12** is a block diagram **1200** illustrating a software architecture **1202**, which can be installed on any one or more of the devices described herein. The software architecture **1202** is supported by hardware such as a machine **1204** that includes processors **1206**, memory **1208**, and I/O components **1210**. In this example, the software architecture **1202** can be conceptualized as a stack of layers, where each layer provides a particular functionality. The software architecture **1202** includes layers such as an operating system **1212**, libraries **1214**, frameworks **1216**, and applications **1218**. Operationally, the applications **1218** invoke API calls **1220** through the software stack and receive messages **1222** in response to the API calls **1220**.

The operating system **1212** manages hardware resources and provides common services. The operating system **1212** includes, for example, a kernel **1224**, services **1226**, and drivers **1228**. The kernel **1224** acts as an abstraction layer between the hardware and the other software layers. For example, the kernel **1224** provides memory management, processor management (e.g., scheduling), component management, networking, and security settings, among other functionalities. The services **1226** can provide other common services for the other software layers. The drivers **1228** are responsible for controlling or interfacing with the underlying hardware. For instance, the drivers **1228** can include display drivers, camera drivers, BLUETOOTH® or BLUETOOTH® Low Energy drivers, flash memory drivers, serial communication drivers (e.g., USB drivers), WI-FI® drivers, audio drivers, power management drivers, and so forth.

The libraries **1214** provide a common low-level infrastructure used by the applications **1218**. The libraries **1214** can include system libraries **1230** (e.g., C standard library) that provide functions such as memory allocation functions, string manipulation functions, mathematic functions, and the like. In addition, the libraries **1214** can include API libraries **1232** such as media libraries (e.g., libraries to support presentation and manipulation of various media formats such as Moving Picture Experts Group-4 (MPEG4), Advanced Video Coding (H.264 or AVC), Moving Picture Experts Group Layer-3 (MP3), Advanced Audio Coding (AAC), Adaptive Multi-Rate (AMR) audio codec, Joint Photographic Experts Group (JPEG or JPG), or Portable Network Graphics (PNG)), graphics libraries (e.g., an OpenGL framework used to render in 2D and 3D in a graphic content on a display), database libraries (e.g., SQLite to provide various relational database functions), web libraries (e.g., WebKit to provide web browsing functionality), and the like. The libraries **1214** can also include a wide variety of other libraries **1234** to provide many other APIs to the applications **1218**.

The frameworks **1216** provide a common high-level infrastructure that is used by the applications **1218**. For example, the frameworks **1216** provide various GUI functions, high-level resource management, and high-level location services. The frameworks **1216** can provide a broad spectrum of other APIs that can be used by the applications **1218**, some of which may be specific to a particular operating system or platform.

In an example, the applications **1218** may include a home application **1236**, a contacts application **1238**, a browser application **1240**, a book reader application **1242**, a location application **1244**, a media application **1246**, a messaging application **1248**, a game application **1250**, and a broad assortment of other applications such as a third-party application **1252**. The applications **1218** are programs that execute functions defined in the programs. Various programming languages can be employed to create one or more of the applications **1218**, structured in a variety of manners, such as object-oriented programming languages (e.g., Objective-C, Java, or C++) or procedural programming languages (e.g., C or assembly language). In a specific example, the third-party application **1252** (e.g., an application developed using the ANDROID™ or IOS™ SDK by an entity other than the vendor of the particular platform) may be mobile software running on a mobile operating system such as IOS™, ANDROID™, WINDOWS® Phone, or another mobile operating system. In this example, the third-party application **1252** can invoke the API calls **1220** provided by the operating system **1212** to facilitate functionalities described herein.

## System with Head-Wearable Apparatus

FIG. **13** illustrates a system **1300** including a head-wearable apparatus **116** with a selector input device, according to some examples. FIG. **13** is a high-level functional block diagram of an example head-wearable apparatus **116** communicatively coupled to a mobile device **114** and various server systems **1304** (e.g., the interaction server system **110**) via various networks **1316**.

The head-wearable apparatus **116** includes one or more cameras, each of which may be, for example, a visible light camera **1306**, an infrared emitter **1308**, and an infrared camera **1310**.

The mobile device **114** connects with head-wearable apparatus **116** using both a low-power wireless connection **1312** and a high-speed wireless connection **1314**. The mobile device **114** is also connected to the server system **1304** and the network **1316**.

The head-wearable apparatus **116** further includes two image displays of optical assembly **1318**. The two image displays of optical assembly **1318** include one associated with the left lateral side and one associated with the right lateral side of the head-wearable apparatus **116**. The head-wearable apparatus **116** also includes an image display driver **1320**, an image processor **1322**, low-power circuitry **1324**, and high-speed circuitry **1326**. The image display of optical assembly **1318** is for presenting images and videos, including an image that can include a GUI, to a user of the head-wearable apparatus **116**.

The image display driver **1320** commands and controls the image display of optical assembly **1318**. The image display driver **1320** may deliver image data directly to the image display of optical assembly **1318** for presentation or may convert the image data into a signal or data format suitable for delivery to the image display device. For example, the image data may be video data formatted according to compression formats, such as H.264 (MPEG-4 Part 10), HEVC, Theora, Dirac, RealVideo RV40, VP8, VP9, or the like, and still image data may be formatted according to compression formats such as PNG, JPEG, Tagged Image File Format (TIFF) or exchangeable image file format (EXIF) or the like.

The head-wearable apparatus **116** includes a frame and stems (or temples) extending from a lateral side of the frame. The head-wearable apparatus **116** further includes a user input device **1328** (e.g., touch sensor or push button), including an input surface on the head-wearable apparatus **116**. The user input device **1328** (e.g., touch sensor or push button) is to receive from the user an input selection to manipulate the GUI of the presented image.

The components shown in FIG. **13** for the head-wearable apparatus **116** are located on one or more circuit boards, for example a PCB or flexible PCB, in the rims or temples. Alternatively, or additionally, the depicted components can be located in the chunks, frames, hinges, or bridge of the head-wearable apparatus **116**. Left and right visible light cameras **1306** can include digital camera elements such as a complementary metal oxide-semiconductor (CMOS) image sensor, charge-coupled device, camera lenses, or any other respective visible or light-capturing elements that may be used to capture data, including images of scenes with unknown objects.

The head-wearable apparatus **116** includes a memory **1302**, which stores instructions to perform a subset or all of the functions described herein. The memory **1302** can also include a storage device.

As shown in FIG. **13**, the high-speed circuitry **1326** includes a high-speed processor **1330**, a memory **1302**, and high-speed wireless circuitry **1332**. In some examples, the image display driver **1320** is coupled to the high-speed circuitry **1326** and operated by the high-speed processor **1330** in order to drive the left and right image displays of the image display of optical assembly **1318**. The high-speed processor **1330** may be any processor capable of managing high-speed communications and operation of any general computing system needed for the head-wearable apparatus

136. The high-speed processor **1330** includes processing resources needed for managing high-speed data transfers on a high-speed wireless connection **1314** to a wireless local area network (WLAN) using the high-speed wireless circuitry **1332**. In certain examples, the high-speed processor **1330** executes an operating system such as a LINUX operating system or other such operating system of the head-wearable apparatus **116**, and the operating system is stored in the memory **1302** for execution. In addition to any other responsibilities, the high-speed processor **1330** executing a software architecture for the head-wearable apparatus **116** is used to manage data transfers with high-speed wireless circuitry **1332**. In certain examples, the high-speed wireless circuitry **1332** is configured to implement Institute of Electrical and Electronic Engineers (IEEE) 802.11 communication standards, also referred to herein as WiFi. In some examples, other high-speed communications standards may be implemented by the high-speed wireless circuitry **1332**.

Low-power wireless circuitry **1334** and the high-speed wireless circuitry **1332** of the head-wearable apparatus **136** can include short-range transceivers (Bluetooth™) and wireless wide, local, or wide area network transceivers (e.g., cellular or WiFi). Mobile device **114**, including the transceivers communicating via the low-power wireless connection **1312** and the high-speed wireless connection **1314**, may be implemented using details of the architecture of the head-wearable apparatus **116**, as can other elements of the network **1316**.

The memory **1302** includes any storage device capable of storing various data and applications, including, among other things, camera data generated by the left and right visible light cameras **1306**, the infrared camera **1310**, and the image processor **1322**, as well as images generated for display by the image display driver **1320** on the image displays of the image display of optical assembly **1318**. While the memory **1302** is shown as integrated with high-speed circuitry **1326**, in some examples, the memory **1302** may be an independent standalone element of the head-wearable apparatus **116**. In certain such examples, electrical routing lines may provide a connection through a chip that includes the high-speed processor **1330** from the image processor **1322** or low-power processor **1336** to the memory **1302**. In some examples, the high-speed processor **1330** may manage addressing of the memory **1302** such that the low-power processor **1336** will boot the high-speed processor **1330** any time that a read or write operation involving memory **1302** is needed.

As shown in FIG. **13**, the low-power processor **1336** or high-speed processor **1330** of the head-wearable apparatus **136** can be coupled to the camera (visible light camera **1306**, infrared emitter **1308**, or infrared camera **1310**), the image display driver **1320**, the user input device **1328** (e.g., touch sensor or push button), and the memory **1302**.

The head-wearable apparatus **116** is connected to a host computer. For example, the head-wearable apparatus **116** is paired with the mobile device **114** via the high-speed wireless connection **1314** or connected to the server system **1304** via the network **1316**. The server system **1304** may be one or more computing devices as part of a service or network computing system, for example, that includes a processor, a memory, and network communication interface to communicate over the network **1316** with the mobile device **114** and the head-wearable apparatus **116**.

The mobile device **114** includes a processor and a network communication interface coupled to the processor. The network communication interface allows for communication over the network **1316**, low-power wireless connection **1312**, or high-speed wireless connection **1314**. Mobile device **114** can further store at least portions of the instructions for generating binaural audio content in the memory of mobile device **114** to implement the functionality described herein.

Output components of the head-wearable apparatus **116** include visual components, such as a display such as a LCD, a PDP, a LED display, a projector, or a waveguide. The image displays of the optical assembly are driven by the image display driver **1320**. The output components of the head-wearable apparatus **116** further include acoustic components (e.g., speakers), haptic components (e.g., a vibratory motor), other signal generators, and so forth. The input components of the head-wearable apparatus **116**, the mobile device **114**, and server system **1304**, such as the user input device **1328**, may include alphanumeric input components (e.g., a keyboard, a touch screen configured to receive alphanumeric input, a photo-optical keyboard, or other alphanumeric input components), point-based input components (e.g., a mouse, a touchpad, a trackball, a joystick, a motion sensor, or other pointing instruments), tactile input components (e.g., a physical button, a touch screen that provides location and force of touches or touch gestures, or other tactile input components), audio input components (e.g., a microphone), and the like.

The head-wearable apparatus **116** may also include additional peripheral device elements. Such peripheral device elements may include biometric sensors, additional sensors, or display elements integrated with the head-wearable apparatus **116**. For example, peripheral device elements may include any I/O components including output components, motion components, position components, or any other such elements described herein.

For example, the biometric components include components to detect expressions (e.g., hand expressions, facial expressions, vocal expressions, body gestures, or eye-tracking), measure biosignals (e.g., blood pressure, heart rate, body temperature, perspiration, or brain waves), identify a person (e.g., voice identification, retinal identification, facial identification, fingerprint identification, or electroencephalogram-based identification), and the like. The biometric components may include a BMI system that allows communication between the brain and an external device or machine. This may be achieved by recording brain activity data, translating this data into a format that can be understood by a computer, and then using the resulting signals to control the device or machine.

The motion components include acceleration sensor components (e.g., accelerometer), gravitation sensor components, rotation sensor components (e.g., gyroscope), and so forth. The position components include location sensor components to generate location coordinates (e.g., a GPS receiver component), Wi-Fi or Bluetooth™ transceivers to generate positioning system coordinates, altitude sensor components (e.g., altimeters or barometers that detect air pressure from which altitude may be derived), orientation sensor components (e.g., magnetometers), and the like. Such positioning system coordinates can also be received over low-power wireless connections **1312** and high-speed wireless connection **1314** from the mobile device **114** via the low-power wireless circuitry **1334** or high-speed wireless circuitry **1332**.

## Glossary

"Carrier signal" refers, for example, to any intangible medium that is capable of storing, encoding, or carrying instructions for execution by the machine and includes digital or analog communications signals or other intangible media to facilitate communication of such instructions. Instructions may be transmitted or received over a network using a transmission medium via a network interface device.

"Client device" refers, for example, to any machine that interfaces to a communications network to obtain resources from one or more server systems or other client devices. A client device may be, but is not limited to, a mobile phone, desktop computer, laptop, portable digital assistant (PDA), smartphone, tablet, ultrabook, netbook, laptop, multi-processor system, microprocessor-based or programmable consumer electronics, game console, STB, or any other communication device that a user may use to access a network.

"Communication network" refers, for example, to one or more portions of a network that may be an ad hoc network, an intranet, an extranet, a virtual private network (VPN), a local area network (LAN), a WLAN, a wide area network (WAN), a wireless WAN (WWAN), a metropolitan area network (MAN), the Internet, a portion of the Internet, a portion of the Public Switched Telephone Network (PSTN), a plain old telephone service (POTS) network, a cellular telephone network, a wireless network, a Wi-Fi® network, another type of network, or a combination of two or more such networks. For example, a network or a portion of a network may include a wireless or cellular network, and the coupling may be a Code Division Multiple Access (CDMA) connection, a Global System for Mobile communications (GSM) connection, or other types of cellular or wireless coupling. In this example, the coupling may implement any of a variety of types of data transfer technology, such as Single Carrier Radio Transmission Technology (1×RTT), Evolution-Data Optimized (EVDO) technology, General Packet Radio Service (GPRS) technology, Enhanced Data rates for GSM Evolution (EDGE) technology, third Generation Partnership Project (3GPP) including 3G, fourth-generation wireless (4G) networks, Universal Mobile Telecommunications System (UMTS), High Speed Packet Access (HSPA), Worldwide Interoperability for Microwave Access (WiMAX), Long Term Evolution (LTE) standard, others defined by various standard-setting organizations, other long-range protocols, or other data transfer technology.

"Component" refers, for example, to a device, physical entity, or logic having boundaries defined by function or subroutine calls, branch points, APIs, or other technologies that provide for the partitioning or modularization of particular processing or control functions. Components may be combined via their interfaces with other components to carry out a machine process. A component may be a packaged functional hardware unit designed for use with other components and a part of a program that usually performs a particular function of related functions. Components may constitute either software components (e.g., code embodied on a machine-readable medium) or hardware components.

A "hardware component" is a tangible unit capable of performing certain operations and may be configured or arranged in a certain physical manner. In various examples, one or more computer systems (e.g., a standalone computer system, a client computer system, or a server computer system) or one or more hardware components of a computer system (e.g., a processor or a group of processors) may be configured by software (e.g., an application or application portion) as a hardware component that operates to perform certain operations as described herein.

A hardware component may also be implemented mechanically, electronically, or any suitable combination thereof. For example, a hardware component may include dedicated circuitry or logic that is permanently configured to perform certain operations. A hardware component may be a special-purpose processor, such as a field-programmable gate array (FPGA) or an ASIC. A hardware component may also include programmable logic or circuitry that is temporarily configured by software to perform certain operations. For example, a hardware component may include software executed by a general-purpose processor or other programmable processors. Once configured by such software, hardware components become specific machines (or specific components of a machine) uniquely tailored to perform the configured functions and are no longer general-purpose processors. It will be appreciated that the decision to implement a hardware component mechanically, in dedicated and permanently configured circuitry, or in temporarily configured circuitry (e.g., configured by software), may be driven by cost and time considerations. Accordingly, the phrase "hardware component" (or "hardware-implemented component") should be understood to encompass a tangible entity, be that an entity that is physically constructed, permanently configured (e.g., hardwired), or temporarily configured (e.g., programmed) to operate in a certain manner or to perform certain operations described herein.

Considering examples in which hardware components are temporarily configured (e.g., programmed), each of the hardware components need not be configured or instantiated at any one instance in time. For example, where a hardware component comprises a general-purpose processor configured by software to become a special-purpose processor, the general-purpose processor may be configured as respectively different special-purpose processors (e.g., comprising different hardware components) at different times. Software accordingly configures a particular processor or processors, for example, to constitute a particular hardware component at one instance of time and to constitute a different hardware component at a different instance of time. Hardware components can provide information to, and receive information from, other hardware components. Accordingly, the described hardware components may be regarded as being communicatively coupled. Where multiple hardware components exist contemporaneously, communications may be achieved through signal transmission (e.g., over appropriate circuits and buses) between or among two or more of the hardware components. In examples in which multiple hardware components are configured or instantiated at different times, communications between such hardware components may be achieved, for example, through the storage and retrieval of information in memory structures to which the multiple hardware components have access. For example, one hardware component may perform an operation and store the output of that operation in a memory device to which it is communicatively coupled. A further hardware component may then, at a later time, access the memory device to retrieve and process the stored output. Hardware components may also initiate communications with input or output devices, and can operate on a resource (e.g., a collection of information). The various operations of example methods described herein may be performed, at least partially, by one or more processors that are temporarily configured (e.g., by software) or permanently configured to perform the relevant operations. Whether temporarily or permanently configured, such processors may constitute processor-implemented components that operate to perform one or more operations or functions described herein.

As used herein, "processor-implemented component" refers to a hardware component implemented using one or more processors. Similarly, the methods described herein may be at least partially processor-implemented, with a particular processor or processors being an example of hardware. For example, at least some of the operations of a method may be performed by one or more processors or processor-implemented components. Moreover, the one or more processors may also operate to support performance of the relevant operations in a "cloud computing" environment or as a "software as a service" (SaaS). For example, at least some of the operations may be performed by a group of computers (as examples of machines including processors), with these operations being accessible via a network (e.g., the Internet) and via one or more appropriate interfaces (e.g., an API). The performance of certain of the operations may be distributed among the processors, not only residing within a single machine, but deployed across a number of machines. In some examples, the processors or processor-implemented components may be located in a single geographic location (e.g., within a home environment, an office environment, or a server farm). In other examples, the processors or processor-implemented components may be distributed across a number of geographic locations.

"Computer-readable storage medium" refers, for example, to both machine-storage media and transmission media. Thus, the terms include both storage devices/media and carrier waves/modulated data signals. The terms "machine-readable medium," "computer-readable medium," and "device-readable medium" mean the same thing and may be used interchangeably in this disclosure. "Ephemeral message" refers, for example, to a message that is accessible for a time-limited duration. An ephemeral message may be a text, an image, a video and the like. The access time for the ephemeral message may be set by the message sender. Alternatively, the access time may be a default setting or a setting specified by the recipient. Regardless of the setting technique, the message is transitory.

"Machine storage medium" refers, for example, to a single or multiple storage devices and media (e.g., a centralized or distributed database, and associated caches and servers) that store executable instructions, routines and data. The term shall accordingly be taken to include, but not be limited to, solid-state memories, and optical and magnetic media, including memory internal or external to processors. Specific examples of machine-storage media, computer-storage media and device-storage media include non-volatile memory, including by way of example semiconductor memory devices, e.g., erasable programmable read-only memory (EPROM), electrically erasable programmable read-only memory (EEPROM), FPGA, and flash memory devices; magnetic disks such as internal hard disks and removable disks; magneto-optical disks; and CD-ROM and DVD-ROM disks The terms "machine-storage medium," "device-storage medium," "computer-storage medium" mean the same thing and may be used interchangeably in this disclosure.

The terms "machine-storage media," "computer-storage media," and "device-storage media" specifically exclude carrier waves, modulated data signals, and other such media, at least some of which are covered under the term "signal medium." "Non-transitory computer-readable storage medium" refers, for example, to a tangible medium that is capable of storing, encoding, or carrying the instructions for execution by a machine. "Signal medium" refers, for example, to any intangible medium that is capable of storing, encoding, or carrying the instructions for execution by a machine and includes digital or analog communications signals or other intangible media to facilitate communication of software or data. The term "signal medium" shall be taken to include any form of a modulated data signal, carrier wave, and so forth. The term "modulated data signal" means a signal that has one or more of its characteristics set or changed in such a matter as to encode information in the signal. The terms "transmission medium" and "signal medium" mean the same thing and may be used interchangeably in this disclosure.

"User device" refers, for example, to a device accessed, controlled or owned by a user and with which the user interacts perform an action, or interaction on the user device, including interaction with other users or computer systems. "Carrier signal" refers to any intangible medium that is capable of storing, encoding, or carrying instructions for execution by the machine and includes digital or analog communications signals or other intangible media to facilitate communication of such instructions. Instructions may be transmitted or received over a network using a transmission medium via a network interface device. "Client device" refers to any machine that interfaces to a communications network to obtain resources from one or more server systems or other client devices. A client device may be, but is not limited to, a mobile phone, desktop computer, laptop, PDA, smartphone, tablet, ultrabook, netbook, laptop, multi-processor system, microprocessor-based or programmable consumer electronics, game console, STB, or any other communication device that a user may use to access a network.

"Communication network" refers to one or more portions of a network that may be an ad hoc network, an intranet, an extranet, a VPN, a LAN, a WLAN, a WAN, a WWAN, a MAN, the Internet, a portion of the Internet, a portion of the PSTN, a POTS network, a cellular telephone network, a wireless network, a Wi-Fi® network, another type of network, or a combination of two or more such networks. For example, a network or a portion of a network may include a wireless or cellular network, and the coupling may be a CDMA connection, a GSM connection, or other types of cellular or wireless coupling. In this example, the coupling may implement any of a variety of types of data transfer technology, such as 1×RTT, EVDO technology, GPRS technology, EDGE technology, 3GPP including 3G, 4G networks, UMTS, HSPA, WiMAX, LTE standard, others defined by various standard-setting organizations, other long-range protocols, or other data transfer technology.

Components may constitute either software components (e.g., code embodied on a machine-readable medium) or hardware components. A "hardware component" is a tangible unit capable of performing certain operations and may be configured or arranged in a certain physical manner. In various examples, one or more computer systems (e.g., a standalone computer system, a client computer system, or a server computer system) or one or more hardware components of a computer system (e.g., a processor or a group of processors) may be configured by software (e.g., an application or application portion) as a hardware component that operates to perform certain operations as described herein.

A hardware component may also be implemented mechanically, electronically, or any suitable combination thereof. For example, a hardware component may include dedicated circuitry or logic that is permanently configured to perform certain operations. A hardware component may be a special-purpose processor, such as a FPGA or an ASIC. A hardware component may also include programmable logic or circuitry that is temporarily configured by software to perform certain operations. For example, a hardware component may include software executed by a general-purpose processor or other programmable processor. Once configured by such software, hardware components become specific machines (or specific components of a machine) uniquely tailored to perform the configured functions and are no longer general-purpose processors. It will be appreciated that the decision to implement a hardware component mechanically, in dedicated and permanently configured circuitry, or in temporarily configured circuitry (e.g., configured by software), may be driven by cost and time considerations. Accordingly, the phrase "hardware component" (or "hardware-implemented component") should be understood to encompass a tangible entity, be that an entity that is physically constructed, permanently configured (e.g., hardwired), or temporarily configured (e.g., programmed) to operate in a certain manner or to perform certain operations described herein.

The various operations of example methods described herein may be performed, at least partially, by one or more processors that are temporarily configured (e.g., by software) or permanently configured to perform the relevant operations. Whether temporarily or permanently configured, such processors may constitute processor-implemented components that operate to perform one or more operations or functions described herein.

Changes and modifications may be made to the disclosed examples without departing from the scope of the present disclosure. These and other changes or modifications are intended to be included within the scope of the present disclosure, as expressed in the following claims.

What is claimed is:

**1**. A method comprising:

accessing a monocular image depicting an object;

predicting both a volumetric reconstruction tensor of the monocular image and a pose of the object by applying a first machine learning model to the monocular image;

identifying a portion of the pose of the object that corresponds to a point in a canonical space associated with a set of position encoding information;

obtaining a point of the volumetric reconstruction tensor corresponding to the identified portion of the pose;

classifying the obtained point as being inside or outside of a canonical volume by applying a second machine learning model to the obtained point of the volumetric reconstruction tensor together with the set of position encoding information; and

generating a three-dimensional (3D) mesh representing the object in the canonical space in response to classifying the obtained point as being inside or outside of the canonical volume.

**2**. The method of claim **1**, wherein the pose of the object comprises a skeletal representation of the object.

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

selecting the point in the canonical space associated with the set of position encoding information.

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

selecting a second portion of the pose of the object that corresponds to a second point in the canonical space associated with a second set of position encoding information;

obtaining a second point of the volumetric reconstruction tensor corresponding to the second portion of the pose; and

classifying the second point as being inside or outside of the canonical volume by applying the second machine learning model to the second point of the volumetric reconstruction tensor together with the second set of position encoding information.

**5**. The method of claim **4**, further comprising repeating selection of portions of the pose and classification of points of the volumetric reconstruction tensor corresponding to the selected portions of the pose as being inside or outside of the canonical volume for each portion of the canonical volume.

**6**. The method of claim **1**, wherein the set of position encoding information represents different body parts of the canonical volume.

**7**. The method of claim **1**, further comprising training the first and second machine learning models by performing training operations comprising:

obtaining a set of training images depicting objects, each of the set of training images being associated with 3D scans of the objects depicted in the set of training images; and

generating ground truth canonical space representations of the objects depicted in the set of training images by modifying poses of the 3D scans of the objects to correspond to a pose in the canonical space.

**8**. The method of claim **7**, wherein the training operations comprise:

selecting a first training image depicting a first object corresponding to a first of the ground truth canonical space representations of the first object;

predicting both an individual volumetric reconstruction tensor of the monocular image and an individual pose of the first object by applying the first machine learning model to the first training image;

identifying an individual portion of the individual pose of the first object that corresponds to an individual point in the canonical space associated with an individual set of position encoding information;

obtaining an individual point of the individual volumetric reconstruction tensor corresponding to the individual portion;

classifying the individual point as being inside or outside of an individual canonical volume by applying the second machine learning model to the individual point of the volumetric reconstruction tensor together with the individual set of position encoding information; and

generating occupancy loss based on a deviation between a classification resulting from classifying the individual point and a corresponding portion of the first ground truth canonical space representation of the object.

**9**. The method of claim **8**, further comprising updating one or more parameters of the first and second machine learning models based on the occupancy loss.

**10**. The method of claim **8**, further comprising:

generating an individual 3D mesh representing the first object in the canonical space in response to classifying the individual point as being inside or outside of the canonical volume;

posing the individual 3D mesh based on the individual pose of the first object predicted by the first machine learning model; and

computing a posed loss based on a deviation between the posed individual 3D mesh and the 3D scan of the first object.

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

cropping a portion of the monocular image corresponding to a head of the object;

generating, based on the cropped portion of the monocular image, facial landmarks of the head of the object;

predicting a head-specific canonical space reconstruction by applying a head-specific canonical network to the cropped portion based on the generated facial landmarks; and combining the head-specific canonical space reconstruction with the canonical volume corresponding to the object.

**12**. The method of claim **11**, further comprising:

selecting a facial landmark in a head-specific canonical space representation of the object;

identifying a specific portion of the object depicted in the cropped portion of the monocular image that corresponds to the selected facial landmark;

obtaining an individual point of the volumetric reconstruction tensor corresponding to the specific portion;

classifying the obtained individual point as being inside or outside of the head-specific canonical space representation of the object by applying a third machine learning model to the obtained individual point; and

generating the head-specific canonical space reconstruction in response to classifying the obtained individual point as being inside or outside of the head-specific canonical space representation.

**13**. The method of claim **12**, further comprising:

predicting both an additional volumetric reconstruction tensor of the cropped portion of the monocular image and a head pose of the object by applying a fourth machine learning model to the cropped portion of the monocular image, wherein the individual point is obtained from the additional volumetric reconstruction tensor.

**14**. The method of claim **11**, further comprising:

updating a pose of a head region in the canonical volume based on the facial landmarks, wherein the 3D mesh is generated using the canonical volume with the updated pose of the head region.

**15**. The method of claim **11**, wherein the canonical volume represents a full body canonical space reconstruction of the object, further comprising:

identifying a region in which the full body canonical space reconstruction of the object overlaps with the head-specific canonical space reconstruction; and

smoothly deforming the region based on differences between the full body canonical space reconstruction of the object and the head-specific canonical space reconstruction.

**16**. The method of claim **15**, further comprising generating the 3D mesh based on the full body canonical space reconstruction, the head-specific canonical space reconstruction, and the smoothly deformed region.

**17**. The method of claim **1**, further comprising generating an extended reality (XR) object based on the 3D mesh.

**18**. The method of claim **17**, further comprising animating the XR object in a view of a real-world environment captured in real time by a camera of a user system.

**19**. A system comprising:

at least one processor; and

at least one memory component having instructions stored thereon that, when executed by the at least one processor, cause the at least one processor to perform operations comprising:

accessing a monocular image depicting an object;

predicting both a volumetric reconstruction tensor of the monocular image and a pose of the object by applying a first machine learning model to the monocular image;

identifying a portion of the pose of the object that corresponds to a point in a canonical space associated with a set of position encoding information;

obtaining a point of the volumetric reconstruction tensor corresponding to the identified portion of the pose;

classifying the obtained point as being inside or outside of a canonical volume by applying a second machine learning model to the obtained point of the volumetric reconstruction tensor together with the set of position encoding information; and

generating a three-dimensional (3D) mesh representing the object in the canonical space in response to classifying the obtained point as being inside or outside of the canonical volume.

**20**. A non-transitory computer-readable storage medium having stored thereon instructions that, when executed by at least one processor, cause the at least one processor to perform operations comprising:

accessing a monocular image depicting an object;

predicting both a volumetric reconstruction tensor of the monocular image and a pose of the object by applying a first machine learning model to the monocular image;

identifying a portion of the pose of the object that corresponds to a point in a canonical space associated with a set of position encoding information;

obtaining a point of the volumetric reconstruction tensor corresponding to the identified portion of the pose;

classifying the obtained point as being inside or outside of a canonical volume by applying a second machine learning model to the obtained point of the volumetric reconstruction tensor together with the set of position encoding information; and

generating a three-dimensional (3D) mesh representing the object in the canonical space in response to classifying the obtained point as being inside or outside of the canonical volume.

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