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(54) **LEARNING APPARATUS, INFERENCE APPARATUS, LEARNING METHOD, INFERENCE METHOD, NON-TRANSITORY COMPUTER-READABLE STORAGE MEDIUM**

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(57) **ABSTRACT**

A learning apparatus comprises one or more memories storing instructions and one or more processors that execute the instructions to acquire a likelihood map of a specific part in an input image by using a first model for detecting the specific part, acquire a region map representing a region of a specific part of a tracking target in the input image by using a second model for detecting the tracking target, and perform learning of the second model based on a loss obtained based on an element product map obtained by an element product of the likelihood map and the region map and correct answer data indicating a region of a specific part of a tracking target in the input image.

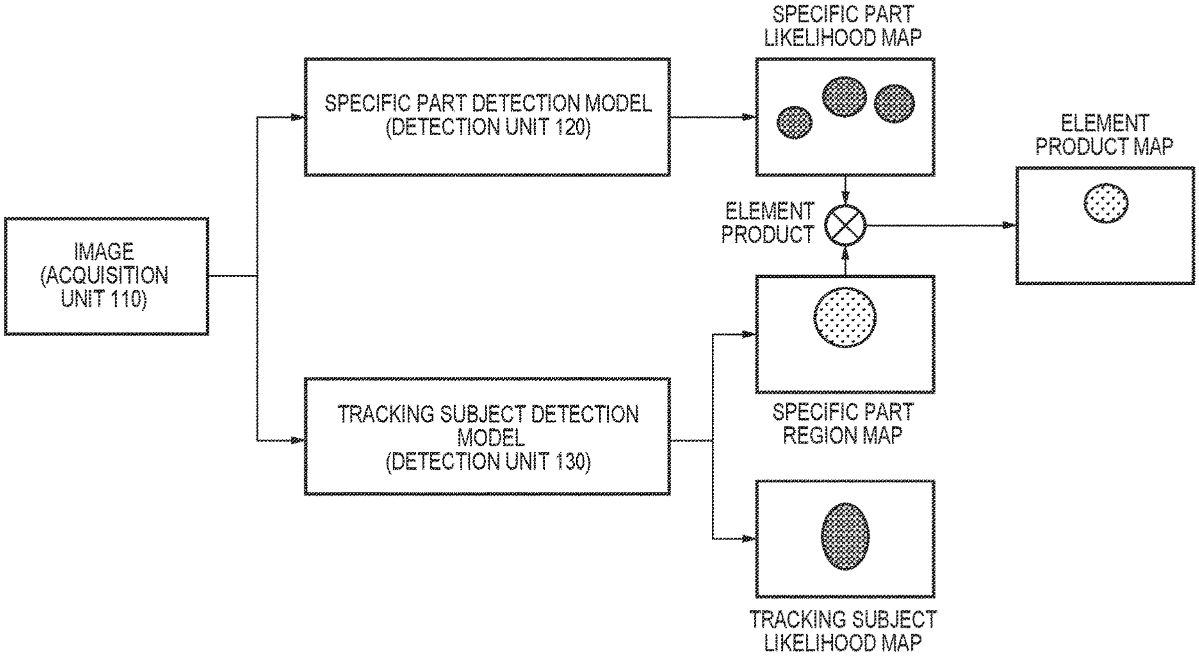

SPECIFIC PART LIKELIHOOD MAP
SPECIFIC PART DETECTION MODEL (DETECTION UNIT 120)
ELEMENT PRODUCT MAP
ELEMENT PRODUCT
IMAGE (ACQUISITION UNIT 110)
TRACKING SUBJECT DETECTION MODEL (DETECTION UNIT 130)
SPECIFIC PART REGION MAP
TRACKING SUBJECT LIKELIHOOD MAP

FIG. 1

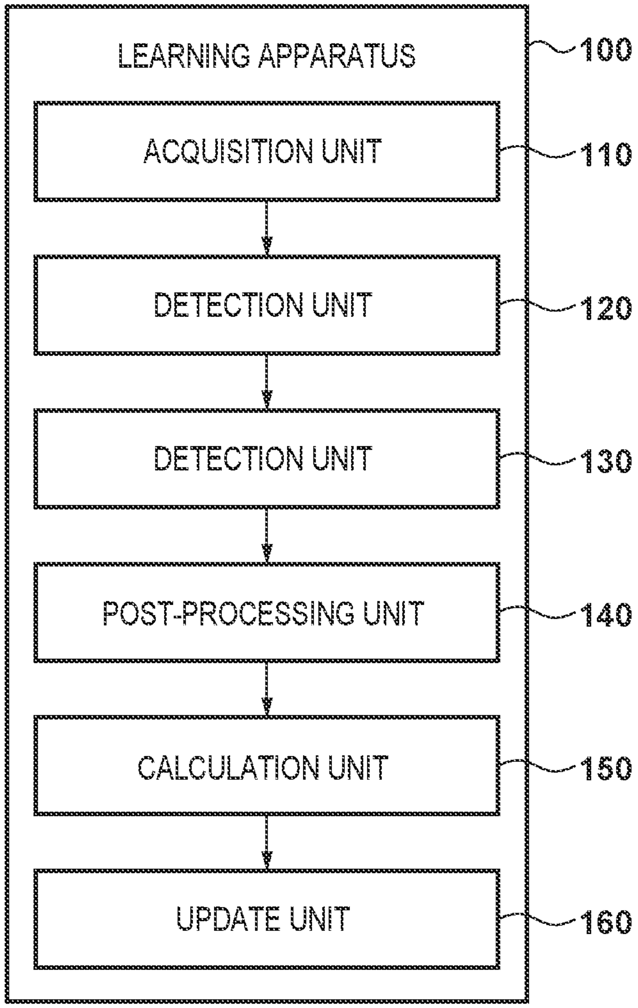

LEARNING APPARATUS
100
ACQUISITION UNIT
110
DETECTION UNIT
120
DETECTION UNIT
130
POST-PROCESSING UNIT
140
CALCULATION UNIT
150
UPDATE UNIT
160

FIG. 2

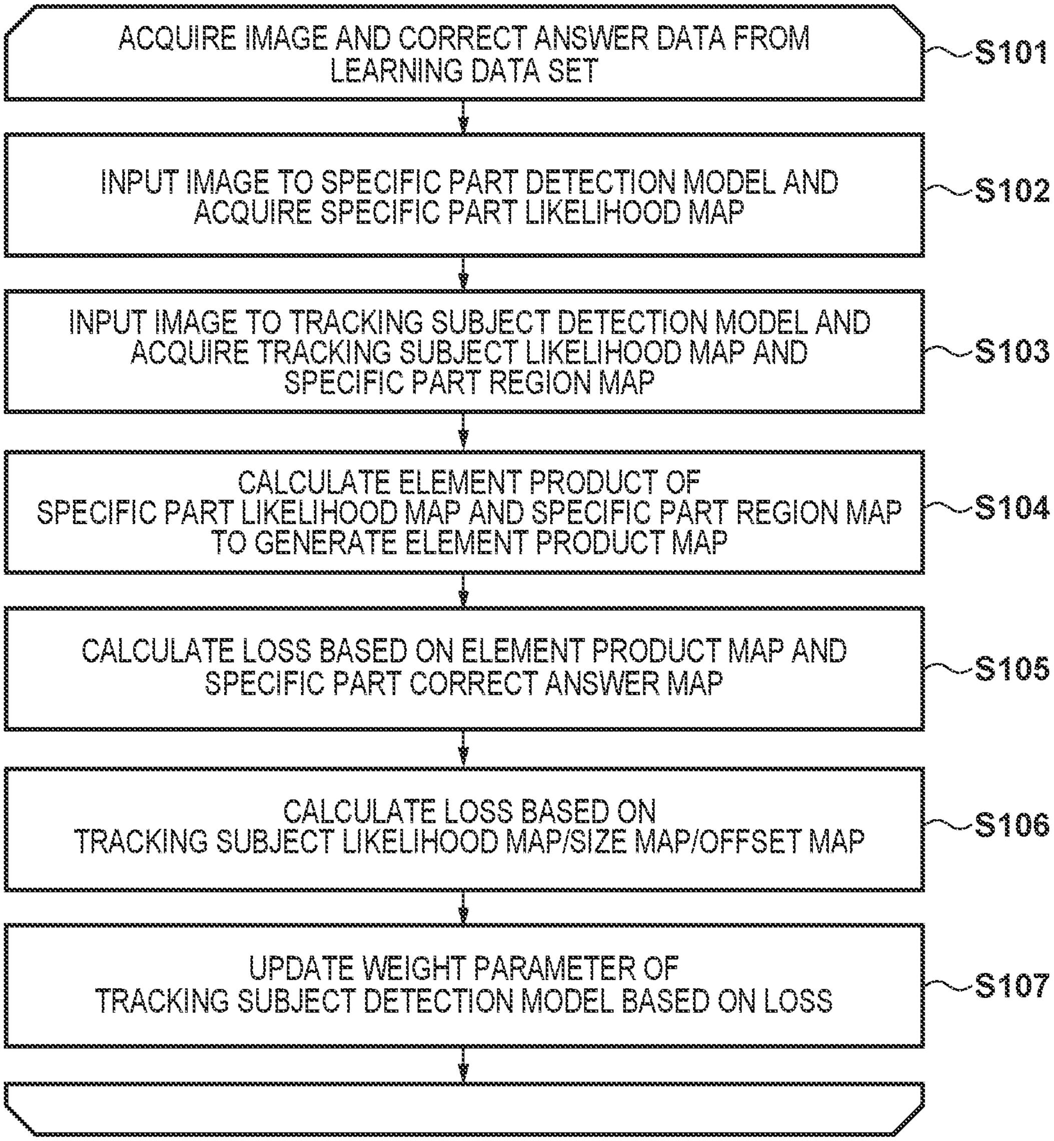

ACQUIRE IMAGE AND CORRECT ANSWER DATA FROM LEARNING DATA SET
S101
INPUT IMAGE TO SPECIFIC PART DETECTION MODEL AND ACQUIRE SPECIFIC PART LIKELIHOOD MAP
S102
INPUT IMAGE TO TRACKING SUBJECT DETECTION MODEL AND ACQUIRE TRACKING SUBJECT LIKELIHOOD MAP AND SPECIFIC PART REGION MAP
S103
CALCULATE ELEMENT PRODUCT OF SPECIFIC PART LIKELIHOOD MAP AND SPECIFIC PART REGION MAP TO GENERATE ELEMENT PRODUCT MAP
S104
CALCULATE LOSS BASED ON ELEMENT PRODUCT MAP AND SPECIFIC PART CORRECT ANSWER MAP
S105
CALCULATE LOSS BASED ON TRACKING SUBJECT LIKELIHOOD MAP/SIZE MAP/OFFSET MAP
S106
UPDATE WEIGHT PARAMETER OF TRACKING SUBJECT DETECTION MODEL BASED ON LOSS
S107

FIG. 3

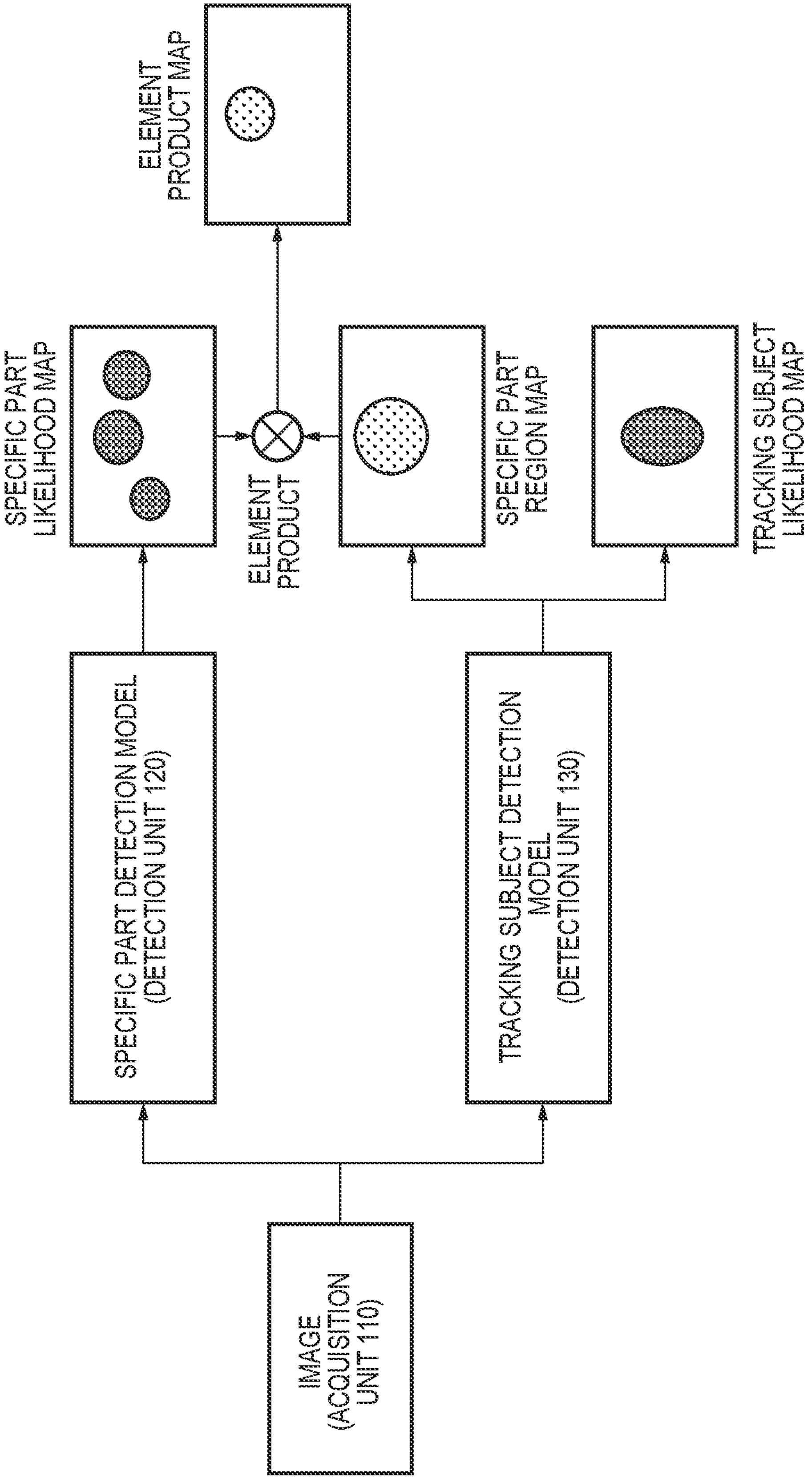


IMAGE
(ACQUISITION
UNIT 110)
SPECIFIC PART DETECTION MODEL
(DETECTION UNIT 120)
TRACKING SUBJECT DETECTION
MODEL
(DETECTION UNIT 130)
SPECIFIC PART
LIKELIHOOD MAP
ELEMENT
PRODUCT
SPECIFIC PART
REGION MAP
TRACKING SUBJECT
LIKELIHOOD MAP
ELEMENT
PRODUCT MAP

FIG. 4

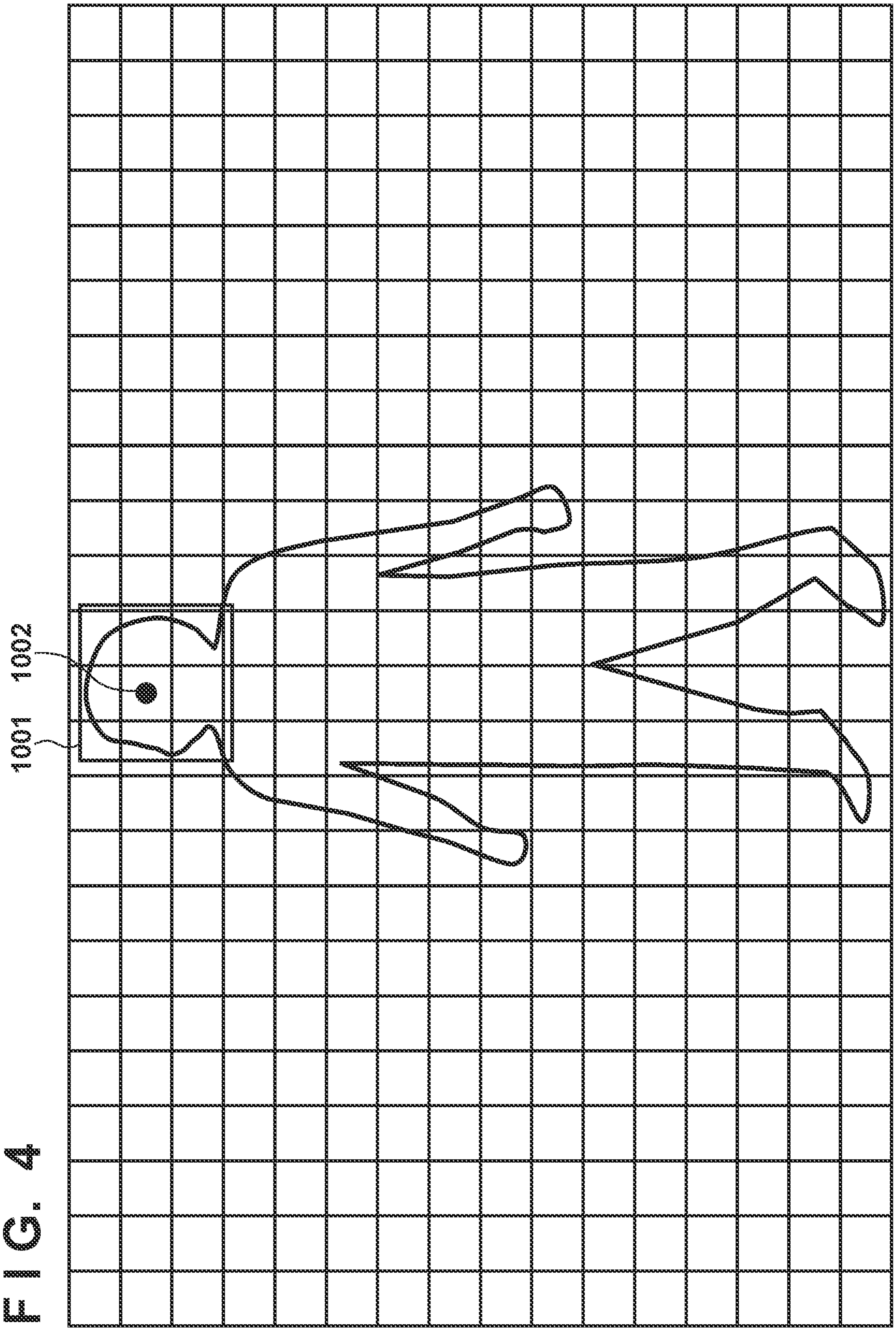


FIG. 5

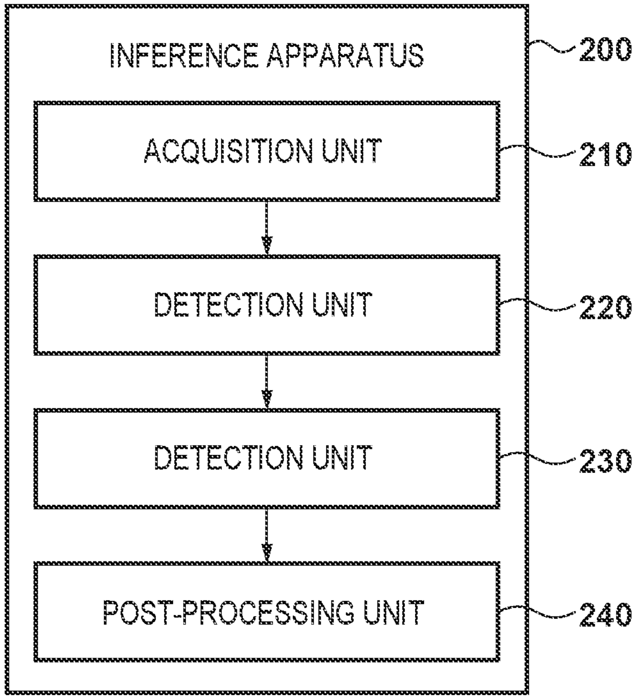

INFERENCE APPARATUS
200
ACQUISITION UNIT
210
DETECTION UNIT
220
DETECTION UNIT
230
POST-PROCESSING UNIT
240

FIG. 6

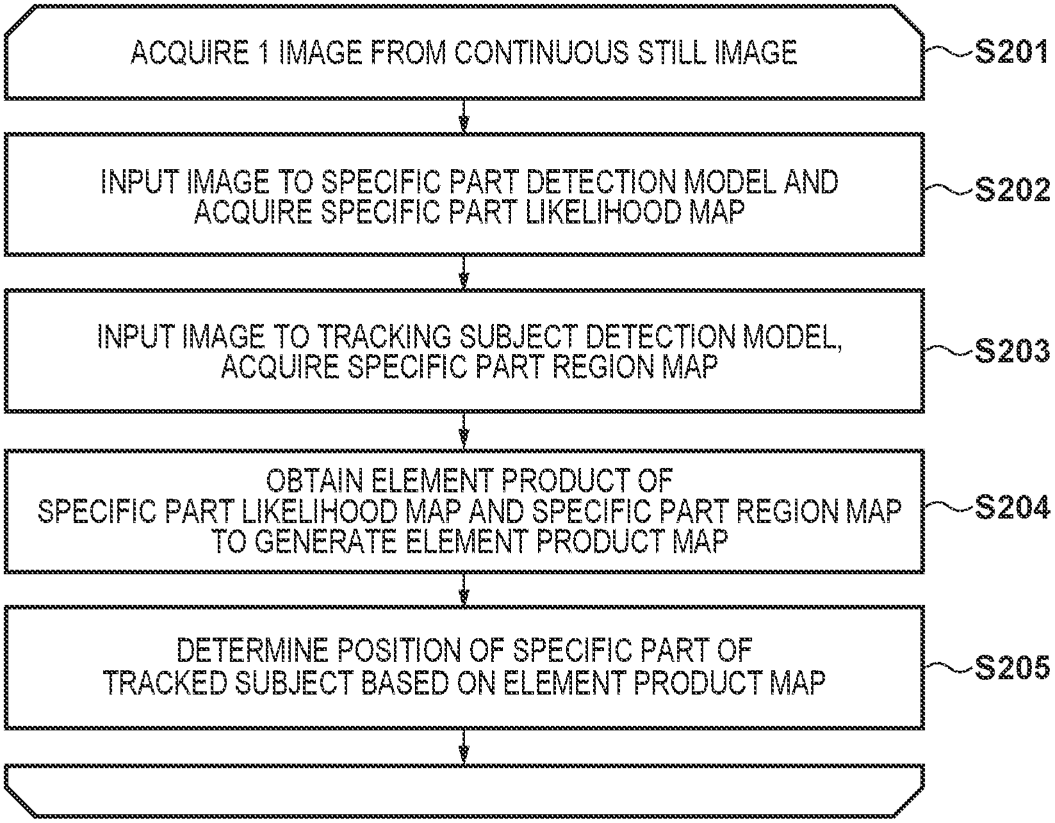

ACQUIRE 1 IMAGE FROM CONTINUOUS STILL IMAGE
S201
INPUT IMAGE TO SPECIFIC PART DETECTION MODEL AND ACQUIRE SPECIFIC PART LIKELIHOOD MAP
S202
INPUT IMAGE TO TRACKING SUBJECT DETECTION MODEL, ACQUIRE SPECIFIC PART REGION MAP
S203
OBTAIN ELEMENT PRODUCT OF SPECIFIC PART LIKELIHOOD MAP AND SPECIFIC PART REGION MAP TO GENERATE ELEMENT PRODUCT MAP
S204
DETERMINE POSITION OF SPECIFIC PART OF TRACKED SUBJECT BASED ON ELEMENT PRODUCT MAP
S205

FIG. 7

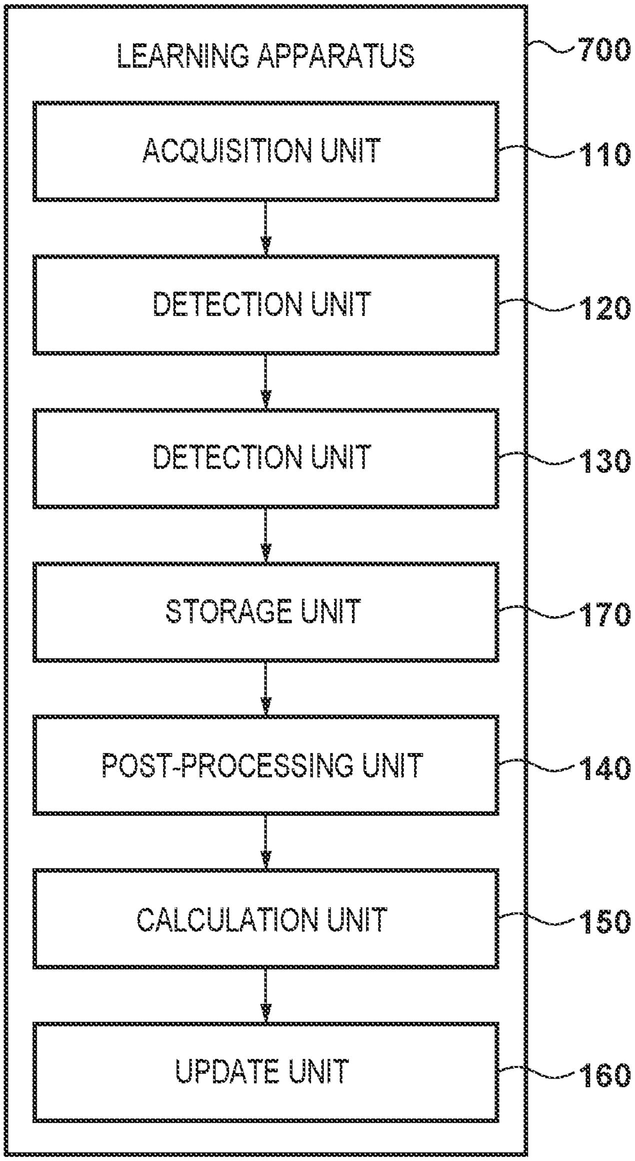

LEARNING APPARATUS
700
ACQUISITION UNIT
110
DETECTION UNIT
120
DETECTION UNIT
130
STORAGE UNIT
170
POST-PROCESSING UNIT
140
CALCULATION UNIT
150
UPDATE UNIT
160

FIG. 8

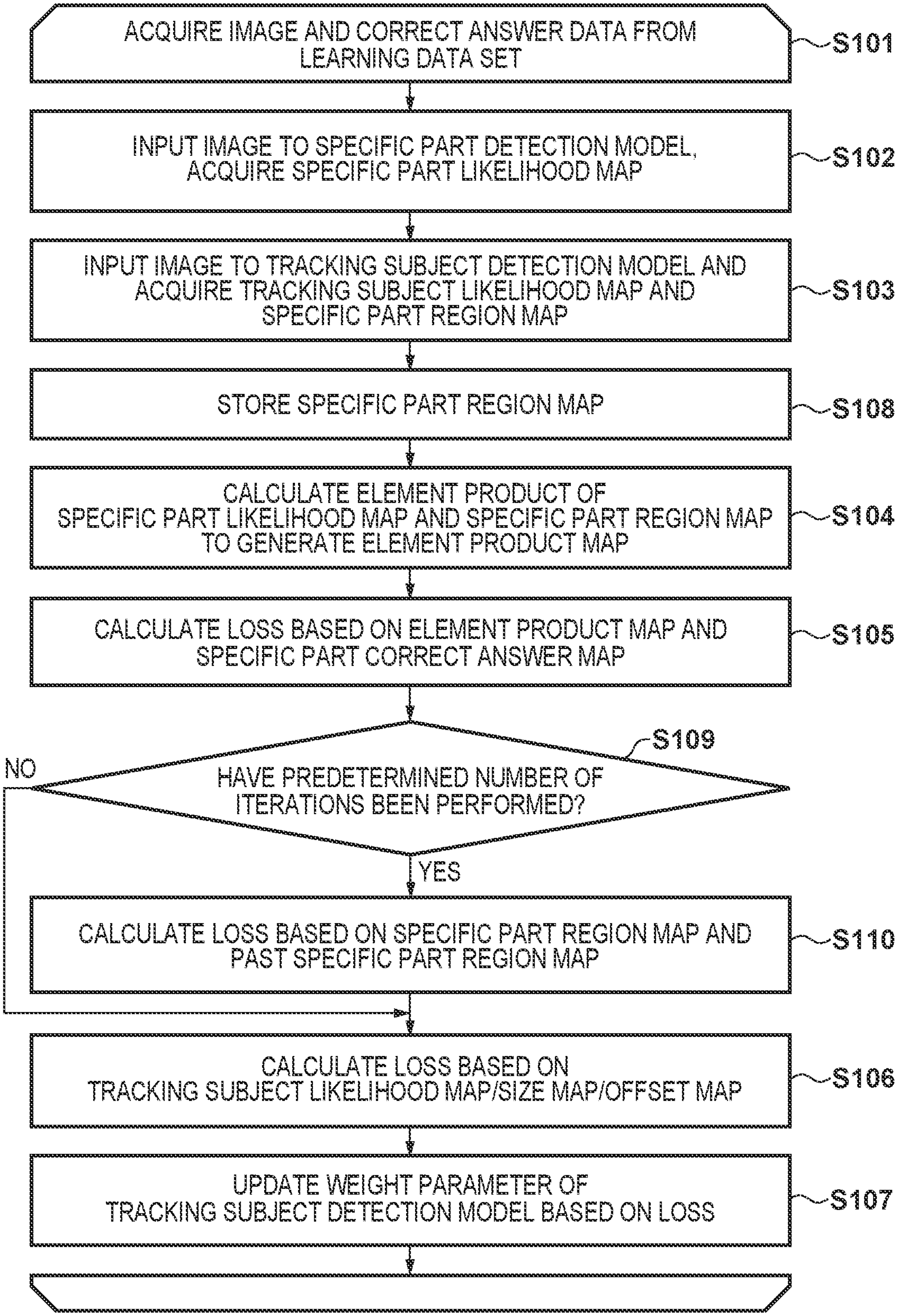
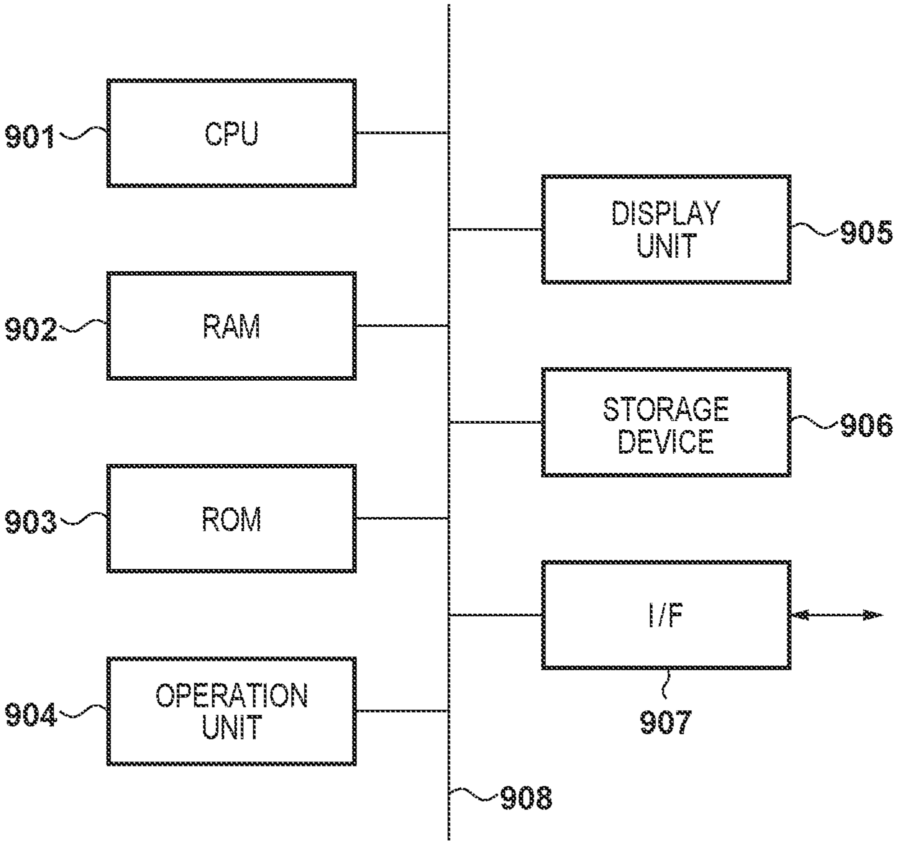

ACQUIRE IMAGE AND CORRECT ANSWER DATA FROM LEARNING DATA SET
S101
INPUT IMAGE TO SPECIFIC PART DETECTION MODEL, ACQUIRE SPECIFIC PART LIKELIHOOD MAP
S102
INPUT IMAGE TO TRACKING SUBJECT DETECTION MODEL AND ACQUIRE TRACKING SUBJECT LIKELIHOOD MAP AND SPECIFIC PART REGION MAP
S103
STORE SPECIFIC PART REGION MAP
S108
CALCULATE ELEMENT PRODUCT OF SPECIFIC PART LIKELIHOOD MAP AND SPECIFIC PART REGION MAP TO GENERATE ELEMENT PRODUCT MAP
S104
CALCULATE LOSS BASED ON ELEMENT PRODUCT MAP AND SPECIFIC PART CORRECT ANSWER MAP
S105
S109
NO
HAVE PREDETERMINED NUMBER OF ITERATIONS BEEN PERFORMED?
YES
CALCULATE LOSS BASED ON SPECIFIC PART REGION MAP AND PAST SPECIFIC PART REGION MAP
S110
CALCULATE LOSS BASED ON TRACKING SUBJECT LIKELIHOOD MAP/SIZE MAP/OFFSET MAP
S106
UPDATE WEIGHT PARAMETER OF TRACKING SUBJECT DETECTION MODEL BASED ON LOSS
S107

FIG. 9


901
CPU
902
RAM
903
ROM
904
OPERATION UNIT
DISPLAY UNIT
905
STORAGE DEVICE
906
I/F
907
908

LEARNING APPARATUS, INFERENCE APPARATUS, LEARNING METHOD, INFERENCE METHOD, NON-TRANSITORY COMPUTER-READABLE STORAGE MEDIUM

BACKGROUND

Field

[0001] The present disclosure relates to a tracking technique.

Description of the Related Art

[0002] As a technique for continuously detecting a specific subject from each frame in a moving image and performing tracking, there is a technique using luminance and color information, a technique using template matching, a technique using a convolutional neural network (CNN), and the like. These techniques are used for a surveillance camera equipped with a function of tracking a subject, a camera equipped with an autofocus function of automatically focusing on a subject, and the like.

[0003] In addition, a technique for detecting a specific part of a subject is also known. It is conceivable that such a technology is used for, for example, focusing on the eyes of a person or an animal of a subject at a pinpoint.

[0004] Such a technique includes a top-down approach of detecting an entire region of a subject and detecting a specific part in the region, and a bottom-up approach of detecting a plurality of specific parts and determining the specific part of the subject by associating them. In the bottom-up approach, when the specific parts are associated with each other, the specific parts may be erroneously associated with a specific part of an object different from the subject. In Japanese Patent Laid-Open No. 2022-510417, the correspondence of each specific part is output by estimating an affinity map representing the correspondence between the specific parts.

[0005] When specific parts of the same object are corresponded with each other from among the separately detected specific parts, the specific parts may be erroneously corresponded with a part of another object present nearby. For example, when the person on the near side and the person on the far side are close to each other on the image, the eyes of the person on the near side may be erroneously corresponded with the eyes of the person on the far side.

SUMMARY

[0006] According to the first aspect of the present invention, there is provided a learning apparatus comprising one or more memories storing instructions and one or more processors that execute the instructions to: acquire a likelihood map of a specific part in an input image by using a first model for detecting the specific part; acquire a region map representing a region of a specific part of a tracking target in the input image by using a second model for detecting the tracking target; and perform learning of the second model based on a loss obtained based on an element product map obtained by an element product of the likelihood map and the region map and correct answer data indicating a region of a specific part of a tracking target in the input image.

[0007] According to the second aspect of the present invention, there is provided an inference apparatus comprising one or more memories storing instructions and one or more processors that execute the instructions to: acquire a likelihood map of a specific part in an input image by using a first model for detecting the specific part; acquire a region map representing a region of a specific part of a tracking target in the input image by using a second model for detecting the tracking target; and detect a position of the specific part in the input image based on an element product map obtained by an element product of the likelihood map and the region map.

[0008] According to the third aspect of the present invention, there is provided a learning method comprising: acquiring a likelihood map of a specific part in an input image by using a first model for detecting the specific part; acquiring a region map representing a region of a specific part of a tracking target in the input image by using a second model for detecting the tracking target; and performing learning of the second model based on a loss obtained based on an element product map obtained by an element product of the likelihood map and the region map and correct answer data indicating a region of a specific part of a tracking target in the input image.

[0009] According to the fourth aspect of the present invention, there is provided an inference method comprising: acquiring a likelihood map of a specific part in an input image by using a first model for detecting the specific part; acquiring a region map representing a region of a specific part of a tracking target in the input image by using a second model for detecting the tracking target; and detecting a position of the specific part in the input image based on an element product map obtained by an element product of the likelihood map and the region map.

[0010] According to the fifth aspect of the present invention, there is provided a non-transitory computer-readable storage medium storing a computer program for causing a computer to function as: a first acquisition unit configured to acquire a likelihood map of a specific part in an input image by using a first model for detecting the specific part; a second acquisition unit configured to acquire a region map representing a region of a specific part of a tracking target in the input image by using a second model for detecting the tracking target; and a learning unit configured to perform learning of the second model based on a loss obtained based on an element product map obtained by an element product of the likelihood map and the region map and correct answer data indicating a region of a specific part of a tracking target in the input image.

[0011] According to the sixth aspect of the present invention, there is provided a non-transitory computer-readable storage medium storing a computer program for causing a computer to function as: a first acquisition unit configured to acquire a likelihood map of a specific part in an input image by using a first model for detecting the specific part; a second acquisition unit configured to acquire a region map representing a region of a specific part of a tracking target in the input image by using a second model for detecting the tracking target; and a detection unit configured to detect a position of the specific part in the input image based on an element product map obtained by an element product of the likelihood map and the region map.

[0012] To provide a technique for correctly associating specific parts of the same object with each other even when another object exists nearby.

[0013] Further features of the present disclosure will become apparent from the following description of exemplary embodiments with reference to the attached drawings.

BRIEF DESCRIPTION OF THE DRAWINGS

[0014] FIG. **1** is a block diagram illustrating an exemplary functional configuration of a learning apparatus **100**;

[0015] FIG. **2** is a flowchart of a learning process of a model by the learning apparatus **100**;

[0016] FIG. **3** is a schematic diagram of processes in steps S**101** to S**103**;

[0017] FIG. **4** is a diagram illustrating an example of a process for obtaining an average vector;

[0018] FIG. **5** is a block diagram illustrating a functional configuration example of an inference apparatus **200**;

[0019] FIG. **6** is a flowchart of a process performed by the inference apparatus **200**;

[0020] FIG. **7** is a block diagram illustrating an exemplary functional configuration of a learning apparatus **700**;

[0021] FIG. **8** is a flowchart of a learning process of the learning apparatus **700**; and

[0022] FIG. **9** is a block diagram illustrating a hardware configuration example of a computer apparatus.

DESCRIPTION OF THE EMBODIMENTS

[0023] Hereinafter, embodiments will be described in detail with reference to the attached drawings. Note, the following embodiments are not intended to limit the scope of the claims. Multiple features are described in the embodiments, but limitation is not made to an embodiment that requires all such features, and multiple such features may be combined as appropriate. Furthermore, in the attached drawings, the same reference numerals are given to the same or similar configurations, and redundant description thereof is omitted.

First Embodiment

[0024] In the present embodiment, a learning apparatus that learns a model for detecting a specific part of a tracking target in an input image will be described. More specifically, in the present embodiment, an example of a learning apparatus that acquires a likelihood map of a specific part in an input image using a first model for detecting the specific part, acquires a region map representing a region of the specific part of the tracking target in the input image using a second model for detecting the tracking target, and performs learning of the second model based on a loss obtained on the basis of an element product map obtained by an element product of the likelihood map and the region map and correct answer data indicating a region of the specific part of the tracking target in the input image will be described.

[0025] FIG. **1** is a block diagram illustrating an exemplary functional configuration of a learning apparatus **100**, according to the present embodiment. A learning process of a model by the learning apparatus **100** according to the present embodiment will be described with reference to the flowchart of FIG. **2**.

[0026] The learning apparatus **100** according to the present embodiment holds a learning data set used in the learning process. The learning data set includes a set of continuous images (continuous image set) and correct answer data corresponding to the images.

[0027] It is assumed that one or more objects including a tracking subject that is a subject serving as a tracking target are captured in each image included in the continuous image set. The continuous image set is, for example, a moving image, and in this case, each frame in the moving image corresponds to the above image.

[0028] The correct answer data includes first region information defining an image region of the tracking subject included in the image corresponding to the correct answer data, and second region information defining an image region of a specific part of the object included in the image.

[0029] In the present embodiment, a case will be described in which the first region information is information indicating the center coordinate of a rectangular region surrounding the image region of the tracking subject and the width and height of the rectangular region. Furthermore, in the present embodiment, a case will be described in which the second region information is information indicating the center coordinate of a rectangular region surrounding the image region of the specific part and the width and height of the rectangular region. In addition, in the present embodiment, a case where the tracking subject is a person and the specific part is a head will be described. Note that the specific parts may be any parts of the object, and the number thereof is not limited to a specific number.

[0030] In step S**101**, an acquisition unit **110** acquires an unselected image and correct answer data corresponding to the image from a learning data set. For example, when the continuous image set is a moving image, the acquisition unit **110** acquires images in order from the head frame, and acquires correct answer data corresponding to the images.

[0031] In step S**102**, a detection unit **120** inputs the image acquired in step S**101** to a specific part detection model and performs a calculation process of the specific part detection model. Here, the specific part detection model is "a learned model configured to output a map (specific part likelihood map) indicating likelihood (likelihood that the pixel position is included in the specific part) corresponding to the pixel position of the input image". As the specific part detection model, a learning model such as CNN or Transformer can be applied, and for example, a learning model disclosed in Single Shot Multibox Detector (ECCV 2016) can be applied. The detection unit **120** acquires "the specific part likelihood map corresponding to the image acquired in step S**101**" that is the output of the specific part detection model by such a calculation process.

[0032] Note that the detection unit **120** may acquire a "size map indicating the size of the specific part included in the image acquired in step S**101**", "offset map representing correction information for correcting the position of a specific part included in the images acquired in step S**101**", or the like using the specific part detection model or other learned models.

[0033] In step S**103**, the detection unit **130** inputs the image acquired in step S**101** to the tracking subject detection model and performs a calculation process of the tracking subject detection model. Here, the tracking subject detection model is a "model learned to output the tracking subject likelihood map and the specific part region map". As the tracking subject detection model, a learning model such as CNN or Transformer can be applied, and for example, the learning model disclosed in Real-Time MDNet (ECCV 2018) can be applied. Here, the tracking subject likelihood map is "a map indicating likelihood corresponding to pixel position of input image (likelihood that pixel position is included in tracking subject)", and the specific part region map is a map indicating a region where the specific part of the tracking subject can exist in the image. The detection unit **130** acquires "a tracking subject likelihood map and a specific part region map corresponding to the images acquired in step S**101**" which is an output of the tracking subject detection model by such a calculation process.

[0034] Note that the detection unit **130** may acquire a "size map indicating the size of the tracking subject included in the image acquired in step S**101**", "offset map representing correction information for correcting the position of the tracking subject included in the images acquired in step S**101**", or the like using the tracking subject detection model or other learned models. The vertical and horizontal sizes of these maps are the same as the vertical and horizontal sizes of the specific part likelihood map.

[0035] In step S**104**, a post-processing unit **140** generates a map obtained by calculating an element product of the specific part likelihood map acquired in step S**102** and the specific part region map acquired in step S**103** as an element product map.

[0036] FIG. **3** shows a schematic diagram of the processes of steps S**101** to S**103**. The image acquired by the acquisition unit **110** is input to the specific part detection model and the tracking subject detection model. A specific part likelihood map is output by a calculation process of the specific part detection model by the detection unit **120** from the specific part detection model. On the other hand, the tracking subject likelihood map and the specific part region map are output by a calculation process of the tracking subject detection model by the detection unit **130** from the tracking subject detection model. Then, the post-processing unit **140** generates a map obtained by calculating the element product of the specific part likelihood map and the specific part region map as the element product map.

[0037] In step S**105**, the calculation unit **150** generates the specific part correct answer map based on the correct answer data acquired in step S**101**, and obtains a loss for the specific part likelihood by using the specific part correct answer map and the element product map generated in step S**104**. Here, the process performed by the calculation unit **150** to generate the specific part correct answer map based on the correct answer data will be described.

[0038] The specific part correct answer map is a map obtained by replacing the second region information included in the correct answer data with a two-dimensional likelihood distribution, and is a map of a correct answer with respect to the specific part likelihood map. Here, it is assumed that a two-dimensional standard normal distribution represented by the following formula (1) is used as the two-dimensional likelihood distribution.

[Equation 1]

$$p(\vec{x}) = \frac{1}{2\pi}\exp\left[-\frac{(\vec{x}-\vec{\mu})^2}{2}\right]\left(\vec{x} = (x, y), \vec{\mu} = (\mu_x, \mu_y)\right) \tag{1}$$

$$\vec{x}$$ [Equation 2]

is a vector representing two dimensional coordinates (x, y) in the specific part correct answer map, and

$$p(\vec{x})$$ [Equation 3]

represents the likelihood at two dimensional coordinates (x, y).

$$\vec{\mu}$$ [Equation 4]

[0039] is an average vector in the specific part correct answer map, and is a vector having μx which is an average value in the x axis direction as an x component and μy which is an average value in the y axis direction as a y component. The calculation unit **150** obtains the average vector using the correct answer data. The process for obtaining the average vector will be described using FIG. **4** by way of an example.

[0040] FIG. **4** is obtained by superimposing the image acquired in step S**101** on a map having the same size as the specific part likelihood map. Here, as an example, the size of the specific part correct answer map is 24 pixels horizontally (element)×16 pixels vertically (element), and the size of the image is 720 pixels horizontally×480 pixels vertically. In the coordinate system, the pixel position at the upper left corner is set as the origin (0,0), the horizontal right direction is set as the positive x axis, and the vertical downward direction is set as the positive y axis. Furthermore, a rectangle **1001** indicates a rectangular region indicated by the second region information included in the correct answer data, a point **1002** indicates the center coordinate of the rectangular region, and here, the center coordinate is (325, 40).

[0041] At this time, as described below, the calculation unit **150** divides the center coordinate (325, 40) by the size ratio between the image and the specific part correct answer map=720/24 (480/16)=30, and converts the result of the division into an integer value by rounding off or the like, and sets the result as an average vector.

[0042] μx: 325/30=10.83 . . . →(rounded off)→11

[0043] μy: 40/30=1.33 . . . →(rounded off)→1

[0044] Average vector μ=(μx, μy)=(11, 1)

[0045] Next, a process performed by the calculation unit **150** to obtain the loss for the specific part likelihood using the specific part correct answer map and the element product map will be described. As the loss function, a cross entropy loss represented by the following formula (2) is used.

[Equation 5]

$$\text{loss} = \frac{1}{N}\sum\left[-M_{gt}\log(M_{inf}) - (1 - M_{gt})\log(1 - M_{inf})\right] \tag{2}$$

[0046] Here, M_{inf} is an element product map, M_{gt} is a specific part correct answer map, and the summation (Σ) is performed for all elements (the number of elements N) of the element product map/specific part correct answer map.

[0047] In step S**106**, the calculation unit **150** obtains a loss with respect to the position and size of the tracking subject based on the map acquired in step S**103** and the correct answer data acquired in step S**101**. The "map acquired in step S**103**" is any one or all of the tracking subject likelihood map, the size map, and the offset map. Since a method of obtaining the loss is known in Real-Time MDNet (ECCV 2018) or the like, the description thereof will be omitted here.

[0048] In step S**107**, the update unit **160** performs a learning process of the tracking subject detection model based on the loss obtained in step S**105** and the loss obtained in step S**106**. For example, the update unit **160** updates the weight parameter of the tracking subject detection model so that the value of the linear sum of the loss obtained in step S**105** and the loss obtained in step S**106** becomes smaller, thereby performing the learning process of the tracking subject detection model. The learning process can be performed using, for example, an error back propagation method.

[0049] Such processes of steps S**101** to S**107** are repeatedly performed until the end condition of the learning process is satisfied. The learning end condition includes, for example, the number of repetitions of the processes of steps S**101** to S**107** being larger than or equal to a threshold value, the value of the linear sum being smaller than or equal to a threshold value, the difference between the previous value and the current value of the linear sum being smaller than or equal to a threshold value, and the like. When the end condition of the learning process is satisfied, the process according to the flowchart of FIG. **2** ends.

[0050] In the present embodiment, one piece of learning data is acquired in one learning process, but a plurality of pieces of learning data may be acquired at a time to perform the learning process. In that case, the processes in steps S**102** to S**106** are performed for each piece of learning data, and the process in step S**107** is performed using the loss calculated for each piece of learning data.

[0051] As described above, in the present embodiment, learning is performed so that the element product map obtained by the element product of the specific part likelihood map and the specific part region map approaches the specific part correct answer map. That is, it can be said that a process of filtering only the specific part of the tracking subject from the specific part of each object is learned using the tracking subject detection model. At this time, the filter process can be performed in consideration of time-series information in which the position of the tracking subject continuously changes between frames by using a tracking subject model learned to detect the same tracking subject from images of different frames. As a result, the discriminability between the objects is enhanced as compared with the case of performing the correspondence of the specific part using the model learned by the independent image having no time-series property, the erroneous correspondence with another object is prevented, and the correspondence accuracy can be improved.

[0052] Note that the learning data set is not limited to being held by the learning apparatus **100**, and may be held by an external apparatus. In this case, the learning apparatus **100** can access the external apparatus and acquire various types of data included in the learning data set.

Second Embodiment

[0053] In the present embodiment, an inference apparatus that detects (infers) the position of the specific part of the tracking subject in the input image using the learned tracking subject detection model generated by the learning apparatus **100** according to the first embodiment will be described.

[0054] FIG. **5** is a block diagram illustrating a functional configuration example of an inference apparatus **200**, according to the present embodiment. The process performed by the inference apparatus **200** to detect a specific part of the tracking subject in the input image using the learned tracking subject detection model generated by the learning apparatus **100** will be described with reference to the flowchart of FIG. **6**. The process according to the flowchart of FIG. **6** illustrates a process performed on an image of one frame, and in a case where the process is performed on images of a plurality of frames, the process according to the flowchart of FIG. **6** is performed on each of the images of the plurality of frames.

[0055] In step S**201**, the acquisition unit **210** acquires an image for one frame. The image acquisition method is not limited to a specific acquisition method, and for example, an image may be acquired from an external apparatus connected to the inference apparatus **200** via a wired/wireless network such as a LAN or the Internet, or an image imaged by the imaging apparatus may be acquired.

[0056] In step S**202**, the detection unit **220** inputs the image acquired in step S**201** to a specific part detection model (a model similar to the specific part detection model used by the learning apparatus **100**) and performs a calculation process of the specific part detection model. The detection unit **220** acquires "the specific part likelihood map corresponding to the image acquired in step S**201**" that is the output of the specific part detection model by such calculation process.

[0057] Note that the detection unit **220** may acquire a "size map indicating the size of the specific part included in the image acquired in step S**201**", "offset map representing correction information for correcting the position of a specific part included in the images acquired in step S**201**", or the like using the specific part detection model or other learned models.

[0058] In step S**203**, the detection unit **230** inputs the image acquired in step S**201** to a tracking subject detection model (a learned tracking subject detection model in the learning apparatus **100**) and performs a calculation process of the tracking subject detection model. The detection unit **230** acquires "the specific part region map corresponding to the image acquired in step S**201**" which is the output of the tracking subject detection model by such a calculation process.

[0059] In step S**204**, a post-processing unit **240** generates a map obtained by calculating an element product of the specific part likelihood map acquired in step S**202** and the specific part region map acquired in step S**203** as an element product map.

[0060] In step S**205**, the post-processing unit **240** detects the position of the specific part of the tracking subject based on the element product map generated in step S**204**. The post-processing unit **240** specifies coordinates (peak coordinates) (xp, yp) of the element having the largest element value in the element product map, multiplies the peak coordinates (xp, yp) by the size ratio described above to convert the coordinates into coordinates on the image, and sets the converted coordinates as the position of the specific part of the tracking subject on the image. The post-processing unit **240** obtains the size ratio by the method described in the first embodiment.

[0061] Furthermore, when the specific part detection model outputs the size map and the offset map, the post-processing unit **240** determines the element value of the element at the peak coordinate in each map to the size/offset of the specific part.

[0062] Note that, although the tracking subject and the specific part (head) are corresponded in the present embodiment, the specific parts of the tracking subject can be corresponded with each other by outputting a plurality of specific part likelihood maps and specific part region maps and corresponding each specific part with the tracking subject.

Third Embodiment

[0063] In the present embodiment, a new loss is added to the loss calculated by the calculation unit **150**. FIG. **7** is a block diagram illustrating a functional configuration example of the learning apparatus **700**, according to the present embodiment. In FIG. **7**, functional units similar to the functional units illustrated in FIG. **1** are denoted by the same reference numerals, and the functional units will not be described or will be briefly described.

[0064] A learning process by the learning apparatus **700** according to the present embodiment will be described with reference to the flowchart of FIG. **8**. In FIG. **8**, processing steps similar to the processing steps illustrated in FIG. **2** are denoted by the same step numbers, and the processing steps will not be described or will be briefly described.

[0065] In step S**108**, the detection unit **130** stores the specific part region map in the storage unit **170**. In step S**109**, the calculation unit **150** determines whether or not the number of times the process according to the flowchart of FIG. **8** is executed is n times or more (iterations of n times or more have been performed). As a result of the determination, in a case where the number of times the process according to the flowchart of FIG. **8** is executed is n times or more, the process proceeds to step S**110**, and in a case where the number of times the process according to the flowchart of FIG. **8** is executed is less than n times, the process proceeds to step S**106**.

[0066] In step S**110**, the calculation unit **150** obtains a loss for the specific part region based on the specific part region map acquired in step S**103** this time and the "specific part region map acquired in past step S**103**" stored in the storage unit **170**.

[0067] The calculation unit **150** first selects a plurality of specific part region maps as the selected specific part region map from the specific part region maps stored in the storage unit **170**. For example, the calculation unit **150** selects, as the selection specific part region map, the specific part region map stored in the storage unit **170** in step S**108** n (n is a natural number of greater than or equal to 2) times before to the specific part region map stored in the storage unit **170** in the previous step S**108**. Then, the calculation unit **150** generates a map obtained by averaging (moving average) the selected n selected specific part region maps as the correct answer specific part region map.

[0068] Then, the calculation unit **150** obtains a loss using the cross entropy loss expressed in the above formula (2) as a loss function. In this step, M_{inf} is the specific part region map acquired in the current step S**103**, and M_{gt} is the correct answer specific part region map.

[0069] In step S**107** according to the present embodiment, in a case where the loss is obtained in step S**110**, the update unit **160** performs the learning process of the tracking subject detection model based on the loss obtained in step S**105**, the loss obtained in step S**106**, and the loss obtained in step S**110**. On the other hand, in a case where step S**110** is skipped, similarly to the first embodiment, the update unit **160** performs the learning process of the tracking subject detection model based on the loss obtained in step S**105** and the loss obtained in step S**106**.

[0070] As described above, in the present embodiment, learning is performed so that the difference between the current specific part region map and the past specific part region map becomes small. That is, it can be said that learning is performed such that the output of the specific part region map is consistent in time series. As a result, it is possible to suppress a large change in the specific part existing region between frames due to an erroneous reaction to an object other than the tracking subject, and to prevent erroneous correspondence with another object. In addition, by using a map calculated from a plurality of past specific part region maps as a correct answer value, in a case where the movement of the tracking subject in the continuous still image is large, the distribution of the calculated correct answer specific part region map has a wide skirt. As a result, learning that allows spread of the distribution of the output specific part region map can be performed, and the region where the specific part can exist can be appropriately estimated even for an object with large movement such as an athlete.

Fourth Embodiment

[0071] The functional units illustrated in FIGS. **1**, **5**, and **7** may be implemented by hardware, and other functional units other than the storage unit **170** may be implemented by software (computer program). In the latter case, the computer apparatus that can execute the computer program is applicable to the learning apparatus **100**, the inference apparatus **200**, and the learning apparatus **700**. A hardware configuration example of a computer apparatus applicable to the learning apparatus **100**, the inference apparatus **200**, and the learning apparatus **700** will be described with reference to a block diagram of FIG. **9**.

[0072] A CPU **901** executes various types of processes using computer programs and data stored in a RAM **902**. As a result, the CPU **901** controls the operation of the entire computer apparatus, and executes or controls various types of processes described as a process performed by a device to which the computer apparatus is applied (learning apparatus **100**, inference apparatus **200**, learning apparatus **700**).

[0073] The RAM **902** includes an area for storing computer programs and data loaded from the ROM **903** or a storage device **906**, or an area for storing data externally received via an I/F **907**. The RAM **902** also has a work area used when the CPU **901** performs various processes. The RAM **902** can thus provide various areas as appropriate.

[0074] The ROM **903** stores setting data of the computer apparatus, computer programs and data related to activation of the computer apparatus, computer programs and data related to basic operations of the computer apparatus, or the like.

[0075] An operation unit **904** is a user interface such as a keyboard, a mouse, and a touch panel screen, and can input various types of instructions to the CPU **901** by a user operation.

[0076] A display unit **905**, having a liquid crystal screen or a touch panel screen, can display results of processing by the CPU **901** via images, characters, or the like. Note that the display unit **905** may be a projection device such as a projector that projects images or characters.

[0077] The external storage device **906** is a large-capacity information storage device such as a hard disk drive device.

The storage device **906** stores a computer program, data, and the like for causing the CPU **901** to execute or control various types of processes described as processes performed by an operating system (OS), the learning apparatus **100**, the inference apparatus **200**, and the learning apparatus **700**. The computer programs and data stored in the storage device **906** are loaded to the RAM **902** as appropriate according to the control by the CPU **901**, which are then subjected to processing by the CPU **901**. Note that the storage unit **170** can be implemented using, for example, the RAM **902** or the storage device **906**.

[0078] The I/F **907** is a communication interface for performing data communication with an external apparatus via a wired/wireless network such as a LAN or the Internet. The CPU **901**, the RAM **902**, the ROM **903**, the operation unit **904**, the display unit **905**, the storage device **906**, and the I/F **907** are all connected to the system bus **908**.

[0079] Note that a computer apparatus having the same configuration may be applied to the learning apparatus and the inference apparatus, or a computer apparatus having different configurations may be applied to the learning apparatus and the inference apparatus.

[0080] Alternatively, the numerical values, processing timings, processing orders, processing entities, and data (information) acquiring method/transmission destination/transmission source/storage location, and the like used in the embodiments described above are referred to by way of an example for specific description, and are not intended to be limited to these examples.

[0081] Alternatively, some or all of the embodiments described above may be used in combination as appropriate. Alternatively, some or all of the embodiments described above may be selectively used.

OTHER EMBODIMENTS

[0082] Embodiment(s) of the present disclosure can also be realized by a computer of a system or apparatus that reads out and executes computer executable instructions (e.g., one or more programs) recorded on a storage medium (which may also be referred to more fully as a 'non-transitory computer-readable storage medium') to perform the functions of one or more of the above-described embodiment(s) and/or that includes one or more circuits (e.g., application specific integrated circuit (ASIC)) for performing the functions of one or more of the above-described embodiment(s), and by a method performed by the computer of the system or apparatus by, for example, reading out and executing the computer executable instructions from the storage medium to perform the functions of one or more of the above-described embodiment(s) and/or controlling the one or more circuits to perform the functions of one or more of the above-described embodiment(s). The computer may comprise one or more processors (e.g., central processing unit (CPU), micro processing unit (MPU)) and may include a network of separate computers or separate processors to read out and execute the computer executable instructions. The computer executable instructions may be provided to the computer, for example, from a network or the storage medium. The storage medium may include, for example, one or more of a hard disk, a random-access memory (RAM), a read only memory (ROM), a storage of distributed computing systems, an optical disk (such as a compact disc (CD), digital versatile disc (DVD), or Blu-ray Disc (BD)™), a flash memory device, a memory card, and the like.

[0083] While the present disclosure has been described with reference to exemplary embodiments, it is to be understood that the disclosure is not limited to the disclosed exemplary embodiments. The scope of the following claims is to be accorded the broadest interpretation so as to encompass all such modifications and equivalent structures and functions.

[0084] This application claims the benefit of Japanese Patent Application No. 2023-024622, filed Feb. 20, 2023, which is hereby incorporated by reference herein in its entirety.

What is claimed is:

1. A learning apparatus comprising one or more memories storing instructions and one or more processors that execute the instructions to:

acquire a likelihood map of a specific part in an input image by using a first model for detecting the specific part;

acquire a region map representing a region of a specific part of a tracking target in the input image by using a second model for detecting the tracking target; and

perform learning of the second model based on a loss obtained based on an element product map obtained by an element product of the likelihood map and the region map and correct answer data indicating a region of a specific part of a tracking target in the input image.

2. The learning apparatus according to claim **1**, wherein the one or more processors execute the instructions to obtain, as the correct answer map, a two dimensional likelihood distribution in which a result obtained by dividing a center coordinate of a region represented by the correct answer data by a size ratio between the correct answer map and the input image is an average vector, and perform learning of the second model based on a loss obtained based on the correct answer map and the element product map.

3. The learning apparatus according to claim **1**, wherein the one or more processors execute the instructions to perform learning of the second model based on the loss and a loss obtained based on the region map and an average of a plurality of region maps acquired in the past.

4. The learning apparatus according to claim **1**, wherein the one or more processors execute the instructions to acquire a likelihood map of the tracking target in the input image using the second model.

5. An inference apparatus comprising one or more memories storing instructions and one or more processors that execute the instructions to:

acquire a likelihood map of a specific part in an input image by using a first model for detecting the specific part;

acquire a region map representing a region of a specific part of a tracking target in the input image by using a second model for detecting the tracking target; and

detect a position of the specific part in the input image based on an element product map obtained by an element product of the likelihood map and the region map.

6. The inference apparatus according to claim **5**, wherein the one or more processors execute the instructions to detect the position of the specific part in the input image based on coordinates of an element having a maximum element value in the element product map.

7. A learning method comprising:

acquiring a likelihood map of a specific part in an input image by using a first model for detecting the specific part;

acquiring a region map representing a region of a specific part of a tracking target in the input image by using a second model for detecting the tracking target; and

performing learning of the second model based on a loss obtained based on an element product map obtained by an element product of the likelihood map and the region map and correct answer data indicating a region of a specific part of a tracking target in the input image.

8. An inference method comprising:

acquiring a likelihood map of a specific part in an input image by using a first model for detecting the specific part;

acquiring a region map representing a region of a specific part of a tracking target in the input image by using a second model for detecting the tracking target; and

detecting a position of the specific part in the input image based on an element product map obtained by an element product of the likelihood map and the region map.

9. A non-transitory computer-readable storage medium storing a computer program for causing a computer to function as:

a first acquisition unit configured to acquire a likelihood map of a specific part in an input image by using a first model for detecting the specific part;

a second acquisition unit configured to acquire a region map representing a region of a specific part of a tracking target in the input image by using a second model for detecting the tracking target; and

a learning unit configured to perform learning of the second model based on a loss obtained based on an element product map obtained by an element product of the likelihood map and the region map and correct answer data indicating a region of a specific part of a tracking target in the input image.

10. A non-transitory computer-readable storage medium storing a computer program for causing a computer to function as:

a first acquisition unit configured to acquire a likelihood map of a specific part in an input image by using a first model for detecting the specific part;

a second acquisition unit configured to acquire a region map representing a region of a specific part of a tracking target in the input image by using a second model for detecting the tracking target; and

a detection unit configured to detect a position of the specific part in the input image based on an element product map obtained by an element product of the likelihood map and the region map.

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