US 20240095951A1

(19) **United States**

(12) **Patent Application Publication**

Ramachandra et al.

(10) **Pub. No.: US 2024/0095951 A1**

(43) **Pub. Date: Mar. 21, 2024**

(54) **POSE PARSERS**

(71) Applicant: **Hinge Health, Inc.**, San Francisco, CA (US)

(72) Inventors: **Bharathkumar Ramachandra**, Montreal (CA); **Paul Anthony Kruszewski**, Westmount (CA)

(21) Appl. No.: **18/515,065**

(22) Filed: **Nov. 20, 2023**

Related U.S. Application Data

(63) Continuation of application No. PCT/IB21/56817, filed on Jul. 27, 2021.

(60) Provisional application No. 63/191,538, filed on May 21, 2021.

Publication Classification

(51) **Int. Cl.**

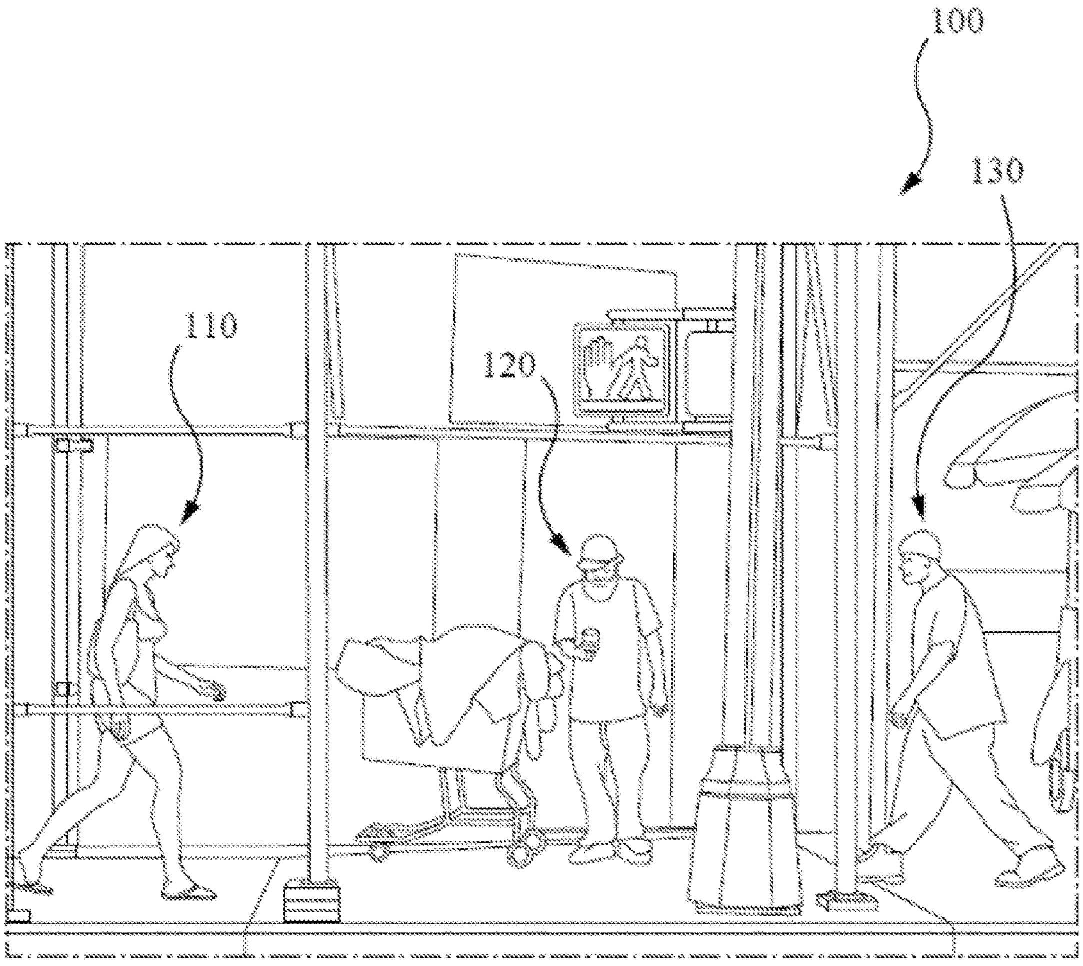
G06T 7/73	(2006.01)
G06V 10/82	(2006.01)
G06V 20/40	(2006.01)
G06V 40/10	(2006.01)

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

CPC ***G06T 7/74*** (2017.01); ***G06V 10/82*** (2022.01); ***G06V 20/41*** (2022.01); ***G06V 40/10*** (2022.01); *G06T 2207/10016* (2013.01); *G06T 2207/20084* (2013.01); *G06T 2207/30196* (2013.01)

(57) **ABSTRACT**

An apparatus is provided an apparatus to estimate poses of multiple objects from a two-dimensional image. The apparatus includes a communications interface to receive raw data from an external source. The raw data includes a representation of a first object and a second object. In addition, the apparatus includes a memory storage unit to store the raw data. The apparatus also includes a first neural network engine to detect parts of the first object and the second object and to generate an intermediate representation of the parts. Furthermore, the apparatus includes a second neural network engine to apply a transformer neural network to the intermediate representation to parse the parts into first object parts and second object parts to generate a first pose of the first object from the first object parts and to generate a second pose of the second object from the second object parts.



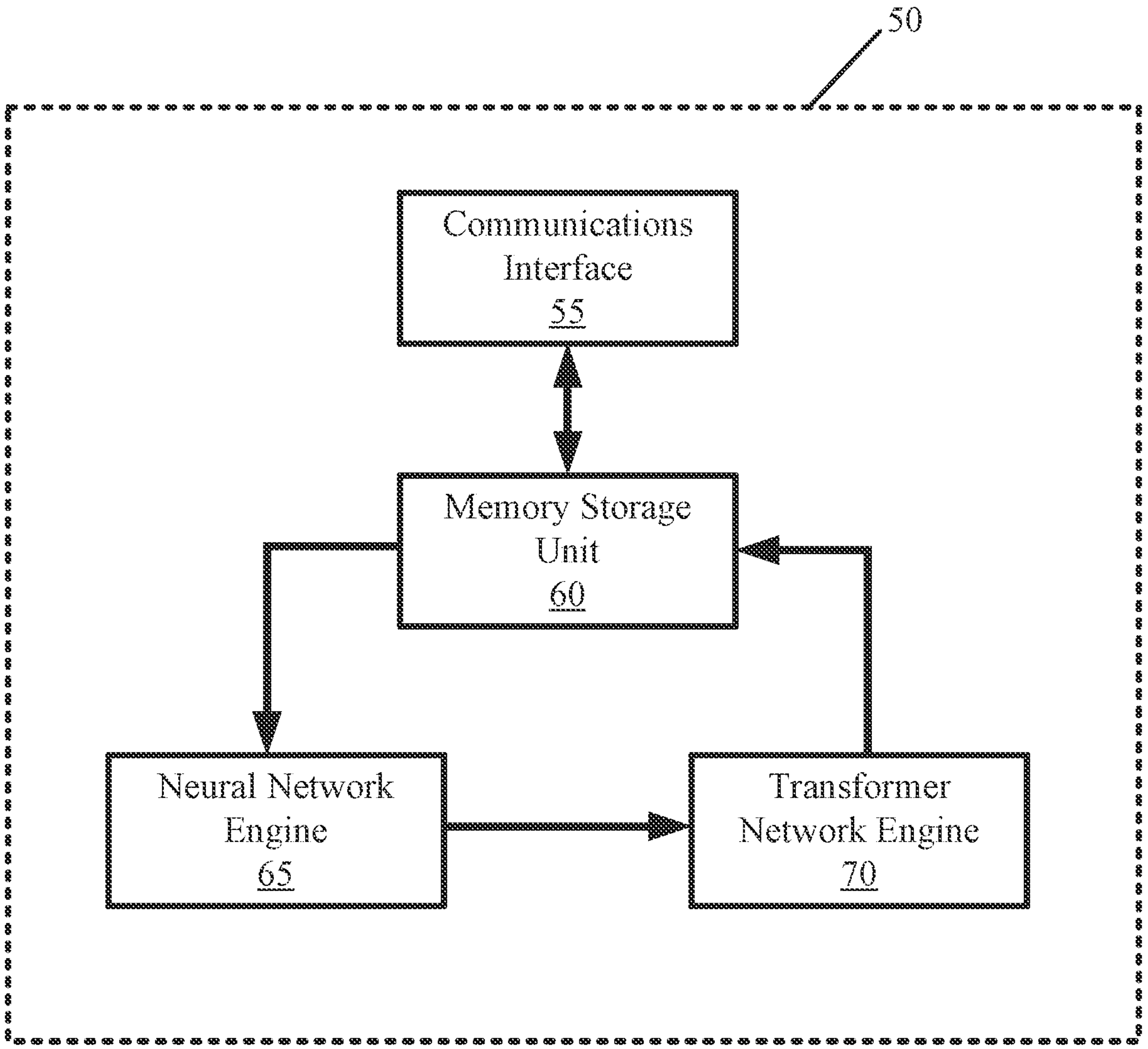

50
Communications Interface
55
Memory Storage Unit
60
Neural Network Engine
65
Transformer Network Engine
70

Fig. 1

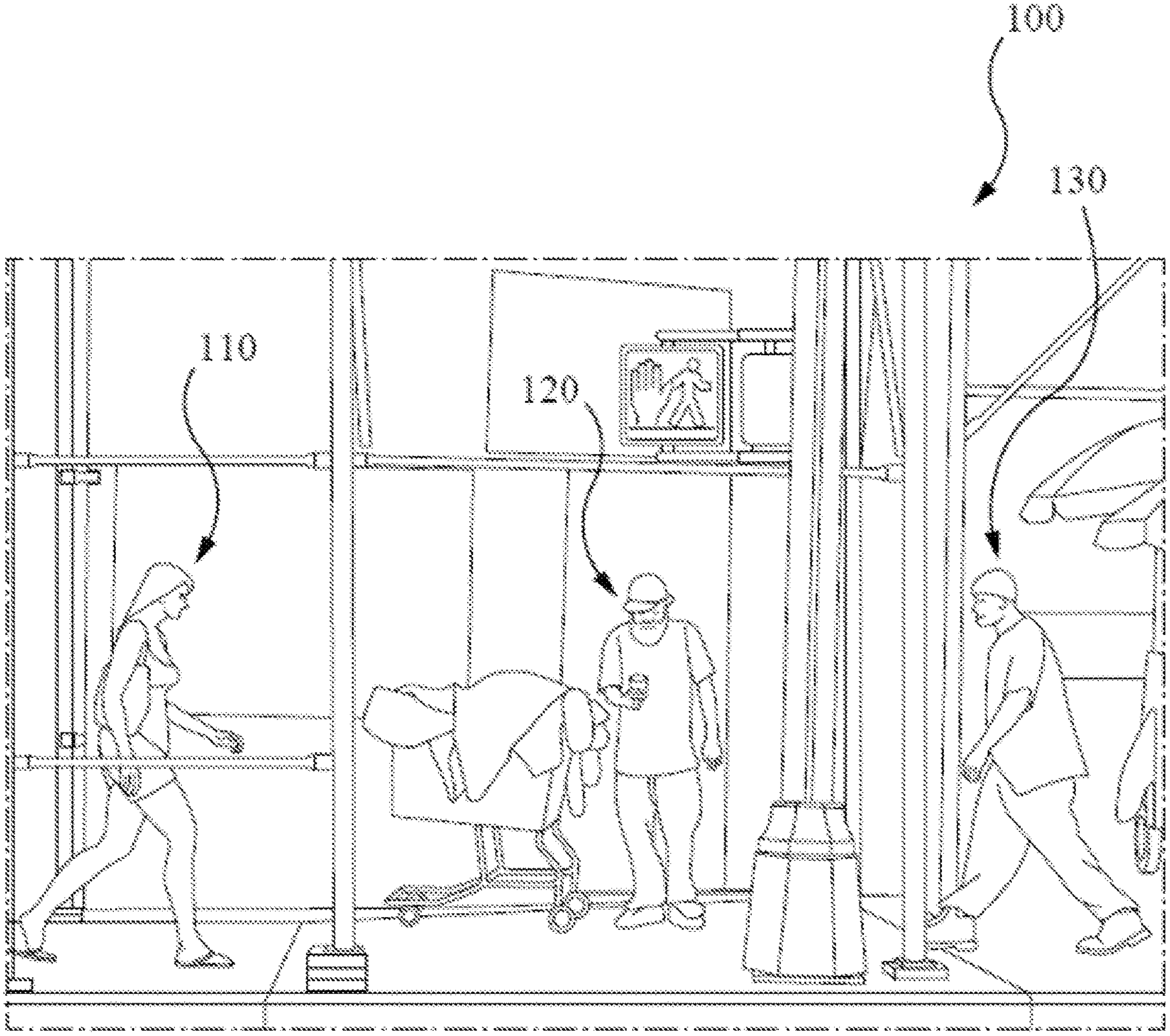


Fig. 2

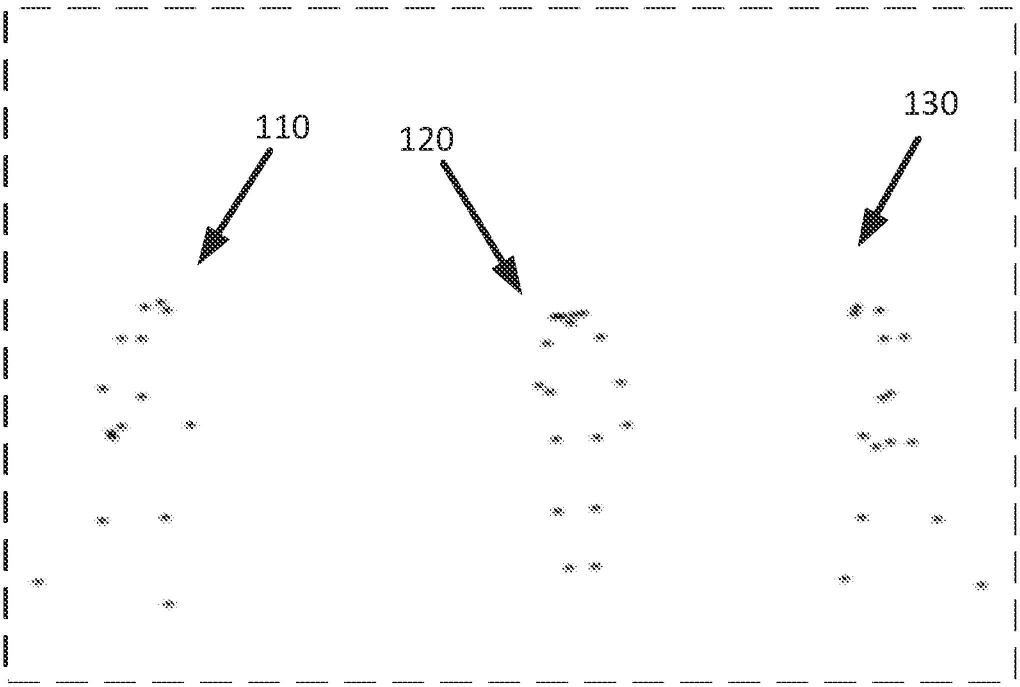


Fig. 3A

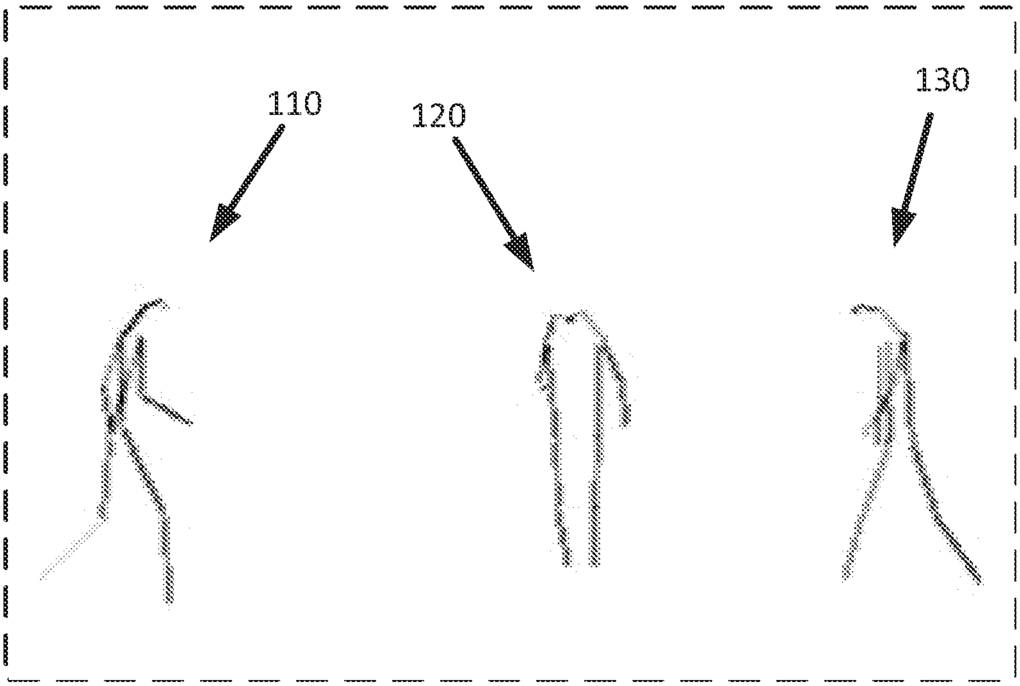


Fig. 3B

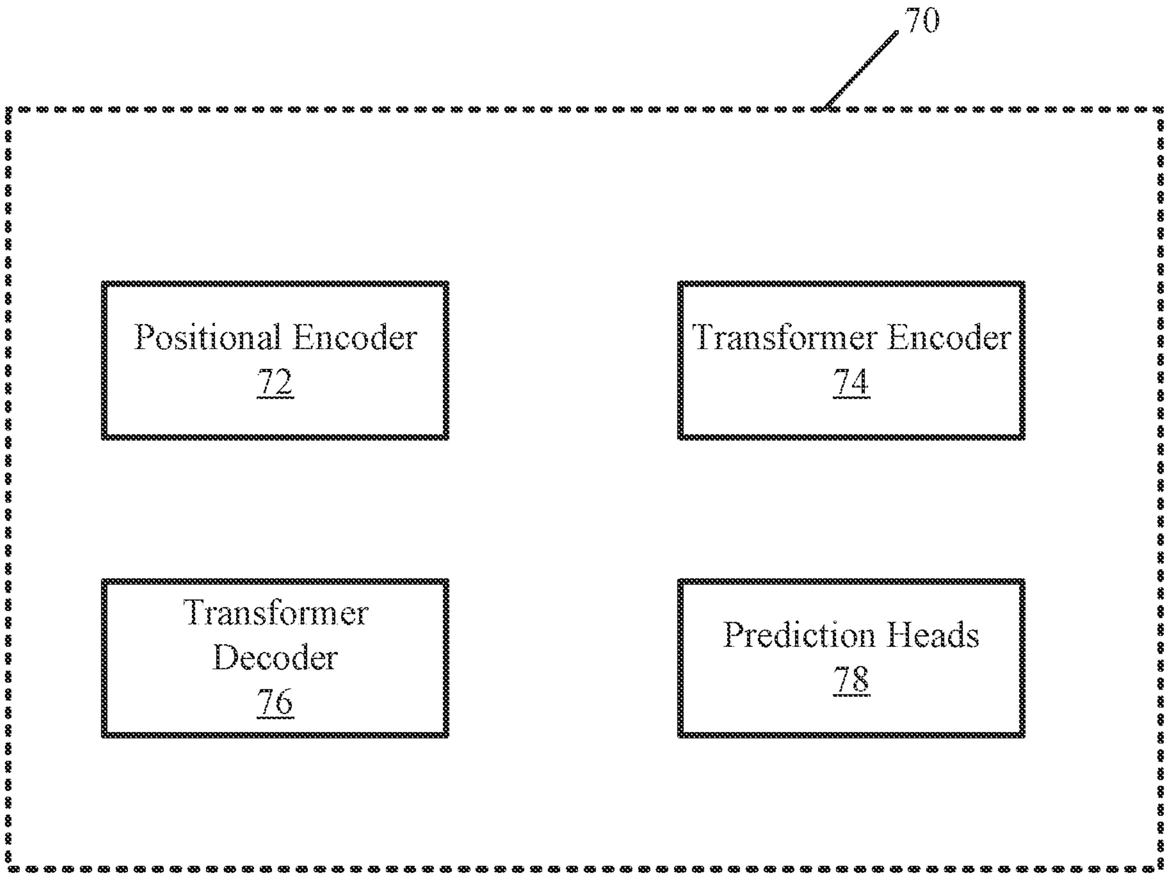

70
Positional Encoder
72
Transformer Encoder
74
Transformer
Decoder
76
Prediction Heads
78

Fig. 4

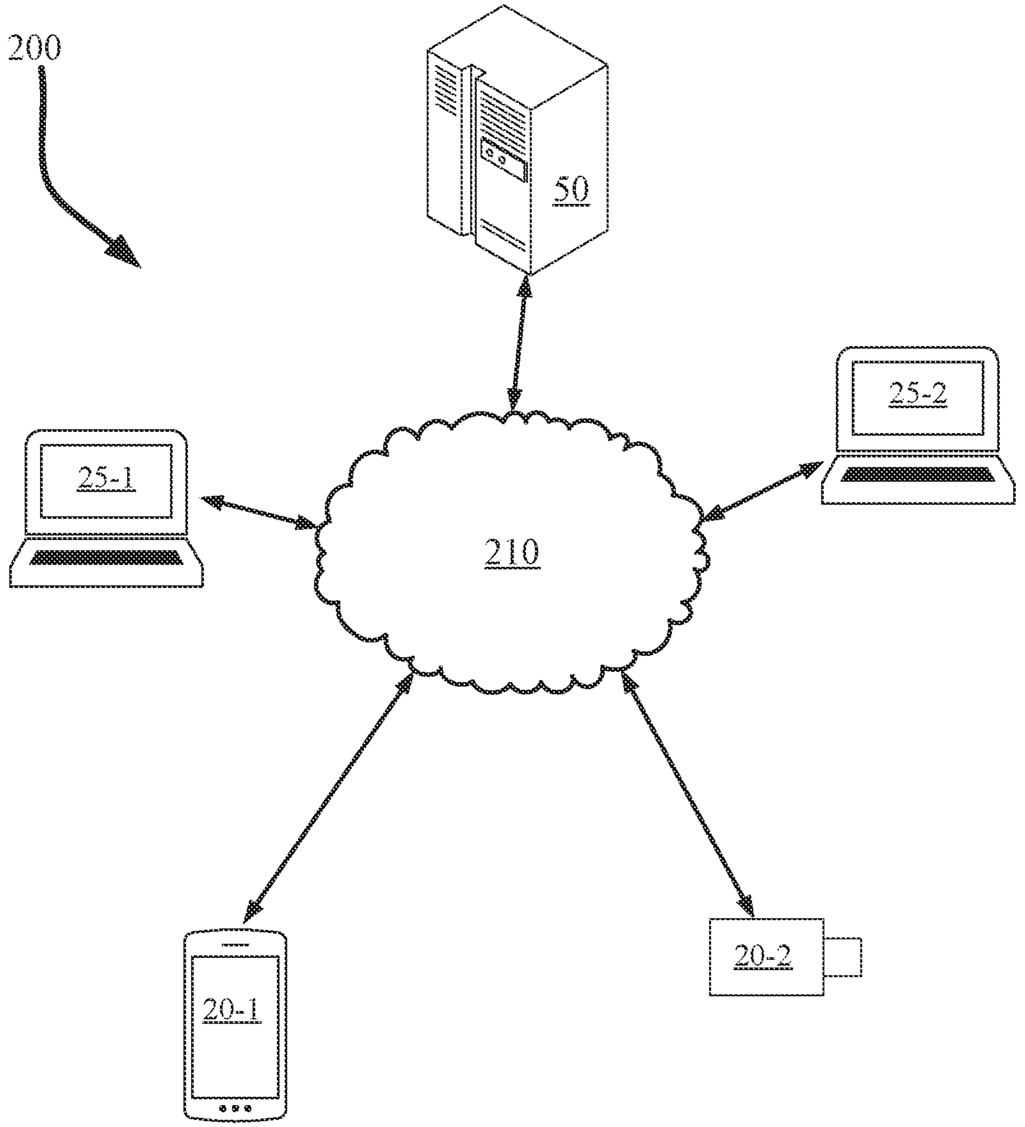


Fig. 5

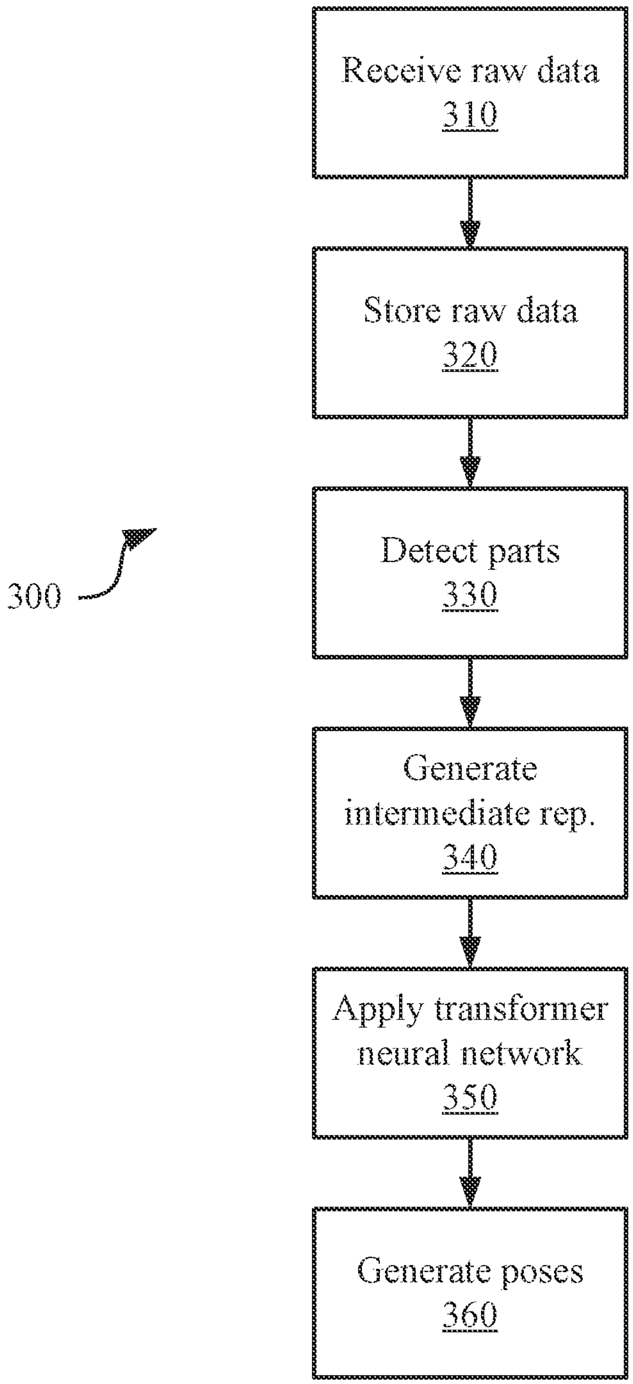

Receive raw data
310
Store raw data
320
Detect parts
330
Generate intermediate rep.
340
Apply transformer neural network
350
Generate poses
360
300

Fig. 6

POSE PARSERS

CROSS-REFERENCE TO RELATED APPLICATIONS

[0001] This application is a continuation of International Patent Application No. PCT/IB2021/056817, filed on Jul. 27, 2021, which claims the benefit of U.S. Provisional Application No. 63/191,538, filed on May 21, 2021, each of which is incorporated herein by reference in its entirety.

BACKGROUND

[0002] Pose parsing to generate a set of poses from a two-dimensional image is known. For example, a hand-designed heuristic algorithm that builds poses from an intermediate representation may be used. In particular, for two-dimensional poses, finding the local peaks in prediction keypoint heatmaps and using the information from predicted bone heatmaps may be used to form connections between keypoints to create poses. In further examples, such as solving the (NP-hard) integer linear programming problem over a fully connected graph or using a recurrent neural network to predict one pose at a time may also be used.

BRIEF DESCRIPTION OF THE DRAWINGS

[0003] Reference Will Now be Made, by Way of Example Only, to the Accompanying Drawings in which:

[0004] FIG. **1** is a schematic representation of the components of an example apparatus to estimate poses of multiple objects from a two-dimensional image;

[0005] FIG. **2** is an example of raw data representing an image received at the apparatus of FIG. **1**;

[0006] FIG. **3**A is a joint heatmap of a combination of a plurality of predefined joints estimated from the image of FIG. **2**;

[0007] FIG. **3**B is a bone heatmap of a combination of a plurality of predefined joints estimated from the image of FIG. **2**;

[0008] FIG. **4** is a schematic representation of an architecture for two-dimensional pose estimation carried out by the transformer network engine;

[0009] FIG. **5** is a schematic representation of a system to provide access to an apparatus to estimate poses of multiple objects from a two-dimensional image; and

[0010] FIG. **6** is a flowchart of an example of a method of estimate poses of multiple objects from a two-dimensional image.

DETAILED DESCRIPTION

[0011] As used herein, any usage of terms that suggest an absolute orientation (e.g. “top”, “bottom”, “up”, “down”, “left”, “right”, “low”, “high”, etc.) may be for illustrative convenience and refer to the orientation shown in a particular Figure. However, such terms are not to be construed in a limiting sense as it is contemplated that various components will, in practice, be utilized in orientations that are the same as, or different than those described or shown.

[0012] Pose parsing is a process used to generate poses of multiple objects from a two-dimensional image. The manner by which this is carried out is not particularly limited and various different methods are used. For images with multiple objects, the identification of the objects and each keypoint or part of an object is to be associated with the correct object. Object pose identification may be used for multiple purposes. For example, objects’ poses may be identified in an image for use in other downstream application. In particular, the identification of an object pose may be used for tracking the object, such as a player on a sport field, to follow the player’s motions and to capture the motions for subsequent playback or analysis.

[0013] A computer implemented method is provided to integrate multiple pose estimation tasks and sub-steps into a single unified system, opening the door for end-to-end training, better use of visual context and reduction of error multiplication induced by multiple steps. It uses a fast, fully differentiable approach carried out on a graphics processing unit to go from an intermediate pose representation to a final fixed set of poses. The set of poses may allow for two-dimension pose, three-dimension pose, appearance estimation and instance segmentation and integration of these outputs into a single unified model that benefits from the synergy between tasks.

[0014] The method provides an improvement over previous “bottom-up” style pose estimation models. For example, the output of the method can be used to extract single object crops for subsequent tasks on a graphics processing unit without transferring intermediary data, such as heatmaps, to a central processing unit for processing, such as the pose parsing. In addition, the method may be faster at inference time than custom designed pose parsing algorithms in use currently. Furthermore, the method provides supervision of the final coordinates of estimated poses, which may improve accuracy of bottom-up methods. The same method may also provide a bottom-up three-dimension pose estimation model to enable a combined bottom-up two-dimension and three-dimension pose estimation model or an instance segmentation model to enable a combined pose estimation plus instance segmentation model or likewise.

[0015] The method may be carried out by an apparatus. The apparatus parses poses in a raw data image without using a separate object detector or (e.g. top-down approaches) or a separate clustering step (e.g. bottom-up approaches). Instead, the apparatus uses a transformer network with positional embeddings and object queries to estimate a variable sized set of output pose coordinates. This is achieved by using an a priori definition of a maximum number of persons (output slots) that can be predicted and having two prediction heads per output slot, one for person/no person binary class prediction and one for pose coordinate prediction. The transformer architecture along with object queries allows parallel decoding of output, as opposed to sequentially predicting one person’s pose at a time. Accordingly, this allows the process to be carried out in parallel on a graphics processing unit instead of transferring the portions of the process, such as part detection, from the graphics processing unit to the central processing unit for pose parsing using conventional algorithms, and subsequent back to the graphics processing unit for further processing in downstream tasks.

[0016] In the present description, the models and techniques discussed below are generally applied to images of persons. It is to be appreciated by a person of skill with the benefit of this description that the examples described below may be applied to other objects as well such as animals and machines.

[0017] Referring to FIG. **1**, a schematic representation of an apparatus to estimate poses of multiple objects from a two-dimensional image is generally shown at **50**. The apparatus **50** may include additional components, such as various additional interfaces and/or input/output devices such as indicators to interact with a user of the apparatus **50**. The interactions may include viewing the operational status of the apparatus **50** or the system in which the apparatus **50** operates, updating parameters of the apparatus **50**, or resetting the apparatus **50**. In the present example, the apparatus **50** is to receive raw data, such as raw data represent an image **100** as shown in FIG. **2**, and to process the raw data to estimate the poses of the objects in the image **100**. In the present example, the apparatus **50** includes a communications interface **55**, a memory storage unit **60**, a neural network engine **65**, and a transformer network engine **70**.

[0018] The communications interface **55** is to communicate with an external source to receive raw data representing an image with multiple target objects. In one specific example, the raw data may represent the image **100** with objects **110**, **120**, **130**, which are the people in the image. Although the raw data received by the communications interface **55** may not represent a complex image in some instances, it is to be appreciated that the apparatus **50** is generally configured to handle complex images which are typically a challenge to handle due to occlusions of the objects in the image. The occlusions are not limited and in some cases, the image may include other objects occluding each other. In other examples, the object may involve occlusions caused other features.

[0019] The manner by which an object is represented and the exact format of the two-dimensional image is not particularly limited. In the present example, the two-dimensional image may be received in an RGB format. It is to be appreciated by a person of skill in the art with the benefit of this description that the two-dimensional image be in a different format, such as a raster graphic file or a compressed image file captured and processed by a camera. Furthermore, the target objects are not particularly limited. In the present example, the target objects are people. In other examples, the target objects may be a subgroup of people, such as people in the foreground. In further examples, the target objects may non-human, such as animals and machines.

[0020] Furthermore, the manner by which the communications interface **55** receives the raw data is not limited. In the present example, the communications interface **55** communicates with external source over a network, which may be a public network shared with a large number of connected devices, such as a WiFi network or cellular network. In other examples, the communications interface **55** may receive data from an external source via a private network, such as an intranet or a wired connection with other devices. In addition, the external source from which the communications interface **55** receives the raw data is not limited to any type of source. For example, the communications interface **55** may connect to another proximate portable electronic device capturing the raw data via a Bluetooth connection, radio signals, or infrared signals. As another example, the communications interface **55** is to receive raw data from a camera system or an external data source, such as the cloud. The raw data received via the communications interface **55** is generally to be stored on the memory storage unit **60**.

[0021] In another example, the apparatus **50** may be part of a portable electronic device, such as a smartphone, that includes a camera system (not shown) to capture the raw data. Accordingly, in this example, the external source may be part of the apparatus **50** and the communications interface **55** may include the electrical connections within the portable electronic device to connect the apparatus **50** portion of the portable electronic device with the camera system. The electrical connections may include various internal buses within the portable electronic device.

[0022] Furthermore, the communications interface **55** may be used to transmit results, such as a pose estimation based on the raw data. For example, the communications interface **55** may be in communication with a downstream service, such as an animation engine (not shown) or pose analyzer. Accordingly, the apparatus **50** may operate to receive raw data from an external source representing multiple objects with complex occlusions to be segmented. In particular, the apparatus **50** may be a portable electronic device, such as a smartphone with a camera, that is capable of capturing an image with the camera and generating a pose of each object in the image.

[0023] The memory storage unit **60** is to store the raw data received via the communications interface **55**. In particular, the memory storage unit **60** may store raw data including two-dimensional images representing objects for which pose estimations are to be generated. In the present example, the memory storage unit **60** may be store multiple two-dimensional images representing different objects in as frame of a video. Accordingly, the raw data may be video data representing the movement of various objects in the image. As a specific example, the objects may be images of people of different sizes and may include the people in different poses showing different keypoints, referred to as joints for people, and having some portions of the body of the person occlude other keypoints and portions of the same body or portions of another body. For example, the image may be of sport scene as shown in the image **100** where multiple players are captured moving about in normal game play. It is to be appreciated by a person of skill that in such a scene, each player may occlude another player.

[0024] Furthermore, the memory storage unit **60** may be used to store addition data. For example, the memory storage unit **60** may store various reference data sources, such as templates and model data, to be used by the neural network engine **65** or the transformer network engine **70**. It is to be appreciated that the memory storage unit **60** may be a physical computer readable medium used to maintain multiple databases, or may include multiple mediums that may be distributed across one or more external servers, such as in a central server or a cloud server.

[0025] In the present example, the memory storage unit **60** is not particularly limited includes a non-transitory machine-readable storage medium that may be any electronic, magnetic, optical, or other physical storage device. As mentioned above, the memory storage unit **60** may be used to store information such as raw data received from external sources via the communications interface **55**, template data, training data, results from the neural network engine **65**, and/or results from the post-processing engine **70**. In addition, the memory storage unit **60** may be used to store instructions for general operation of the apparatus **50**. The memory storage unit **60** may also store an operating system that is executable by a processor to provide general functionality to the apparatus **50** such as functionality to support various applications. The memory storage unit **60** may additionally store instructions to operate the neural network engine **65** and the post-processing engine **70**. Furthermore, the memory storage unit **60** may also store control instructions to operate other components and any peripheral devices that may be installed with the apparatus **50**, such cameras and user interfaces.

[0026] The memory storage unit **60** may be preloaded with data or instructions to operate components of the apparatus **50**. In other examples, the instructions may be loaded via the communications interface **55** or by directly transferring the instructions from a portable memory storage device connected to the apparatus **50**, such as a memory flash drive. In other examples, the memory storage unit **60** may be an external unit such as an external hard drive, or a cloud service providing content.

[0027] The neural network engine **65** is to receive or retrieve the raw data stored in the memory storage unit **60**. The neural network engine **65** subsequently detects parts of the objects in the image represented by the raw data and generates an intermediate representation of the parts that are detected. The manner by which the neural network engine **65** generates the intermediate representation is not particularly limited. In the present example, the neural network engine **65** may apply a convolution neural network to the raw data to generate the intermediate representation. Continuing with the example, the convolution neural network applied by the neural network engine to implement a body part detection model is not limited and may involve any model that may receive an image as input and produce an intermediate representation of body part detections represented as spatial two-dimensional feature maps.

[0028] The intermediate representation is not particularly limited. For example, the neural network engine **65** may generate multiple keypoint heatmaps as the intermediate representation, where each keypoint heatmap represents a keypoint of one of the objects in the image **100**. Referring to FIG. **3**A, the keypoint heatmaps are combined to show the visible keypoints in the image **100**. In particular, it is to be appreciated by a person of skill with the benefit of this description that the combined heatmap shown in FIG. **3**A may be a sum of the keypoint heatmaps values for each keypoint as determined by the neural network engine **65** when overlaid on top of each other.

[0029] The intermediate representation generated by the neural network engine **65** may be a plurality of connector heatmaps represented by part affinity fields, which are vector fields that describe association between parts, the parts being keypoints here. Combining the connector heatmaps may generate an intermediate representation as shown in FIG. **3**B. Referring to FIG. **3**B, the connector heatmaps are combined to show the visible connectors in the image **100**. In particular, it is to be appreciated by a person of skill with the benefit of this description that the combined heatmap shown in FIG. **3**B may be a sum of the connector heatmaps values for each connector as determined by the neural network engine **65** when overlaid on top of each other. In the present example, each connector may represent a "bone" between two keypoints or "joints". It is to be appreciated by a person of skill in the art with the benefit of this description that the terms "joint" and "bone" refer to various reference points in a person that may be modeled with a range of motion to represent an approximation of the reference points on a person. For example, a joint may refer to a reference point on a person that is not a physiological joint, such as an eye. In other examples, a joint may refer to a reference point with multiple physiological bone joints, such as a wrist or ankle. Similarly, a connector or bone may refer to a connection between joints as described herein.

[0030] In other examples, the neural network engine **65** may also generate other intermediate representations. For example, the neural network engine **65** may generate Gaussian bone heatmaps, which is a type of connector heatmap. In this example, the Gaussian bone heatmaps may be represented by additional maps with elliptical Gaussians whose major axes are aligned with the line joining pairs of keypoints.

[0031] As another example, the neural network engine **65** may also generate associative embeddings. In this example, the associative embedding tag map contains a unique ID tag that serves to identify each pixel with the identity of a person in the image. Thus, a pose read-out can be achieved by simply connecting the keypoints that share the same ID tag in the tag map.

[0032] The transformer network engine **70** is to apply a transformer neural network model to the intermediate representation generated by the neural network engine **65**. The transformer neural network architecture is a type of network that may be used to take the intermediate representation of part detections along with a type of connector heatmap or associative embedding map or likewise from the neural network engine and solve a part-to-object association problem to output a fixed set of poses comprised of the parts. In the present example, the transformer network engine **70** uses less computational resources than carrying out complicated calculations to parse the intermediate representations into separate poses of each object in the image using a differentiable and end-to-end trainable manner. Upon parsing the intermediate representations, the transformer network engine **70** generates a plurality of poses, such as a set of ground truth poses corresponding to the objects in the image. Accordingly, the transformer network engine **70** may be executed on a graphics processor unit, such as the same graphics processing unit that carries out the functions of the neural network **65** the instead of transferring the intermediate representations to another processor to carry out more computationally intensive calculations to parse the poses, such as solving an integer linear programming problem over a fully connected graph or executing a recurrent neural network, both of which use more computational resources than the transformer neural network carried out by the transformer network engine **70**.

[0033] Referring to FIG. **4**, the transformer neural network architecture carried out by the transformer network engine **70** is shown in greater detail. In the present example, the transformer network engine **70** may to include a positional encoder **72**, a transformer encoder **74**, a transformer decoder **76**, and prediction heads.

[0034] In the present example, it is to be appreciated by a person of skill with the benefit of this description that the output poses are permutation invariant. The positional encoder **72** injects positional information about the input spatial feature maps in the intermediate representation. The input positional encodings are generated by applying a sum of sine and cosine functions to each of the pixel coordinate maps (x and y) and embedded into the keypoint heatmap by element-wise addition. The output positional encodings are vectors learnt during the learning process and used by the transformer decoder in generating the output.

[0035] The transformer encoder **74** and the transformer decoder **76** process the intermediate representation with the injected positions. In the present example, the transformer encoder **74** is composed of a stack of identical data layers where each layer has two sub-layers. The transformer encoder **74** then applies out a multi-head self-attention mechanism, and a simple, position-wise fully connected feed-forward network. The transformer decoder **76** is also composed of a stack of identical data layers. In addition, the transformer decoder **76** uses output positional encodings/object queries which are leamt from data, to prevent the output heads from competing against each other to process the pose information of a same person in the image. In addition to the two sub-layers in each layer of the transformer encoder **74**, the transformer decoder **76** inserts a third sub-layer, which performs multi-head attention over the output of the stack from the transformer encoder **74**. Similar to the transformer encoder, residual connections around each of the sub-layers, followed by layer normalization is carried out. It is to be appreciated by a person of skill with the benefit of this description that the transformer encoder **74** and the transformer decoder **76** provide the ability to perform global reasoning on the intermediate representation received from the neural network engine **65**. Multi-head self-attention is a module that runs several self-attention mechanisms in parallel. An attention mechanism takes 3 inputs, a query (Q), key (K) and value (V) and performs the operation g(f(Q, K),V). When Q=K=V, the attention mechanism is referred to as self-attention. The particular form of self-attention used here is the scaled dot-product attention function which determines the functions f( ) and g( ).

[0036] In the present example, the number of outputs from the transformer decoder **76** to the prediction heads **78** is to be fixed to a number larger than the maximum expected number of outputs. In examples where the number of objects is greater than number of outputs, a null output token may be added on the excess outputs. Accordingly, this provides the ability to predict poses in an image with an unknown number of objects up to the number of outputs. In the present example, the transformer decoder **76** generates four outputs. However, it is to be appreciated by a person of skill with the benefit of this description that in other examples, the transformer decoder **76** may generate more or less than four outputs.

[0037] In the present example, the transformer decoder **76** generates outputs in parallel rather than sequentially to provide an efficient manner to train and infer from the model in particular, the object queries and/or output positional embeddings act as anchors for the prediction heads **78**. This allows the prediction heads **78** to avoid competing for output predictions from the transformer decoder **76**. Instead, the prediction heads **78** may then specialize in the types of predictions for which they are responsible.

[0038] The transformer network **70** may execute a biparte matching loss operation to be applied to the results from the prediction heads **78** to training this system using labeled pose data. In the present example, the biparte matching loss operation is to solve the stable marriage problem inside the loss function. This results in the correct number of outputs to be emitted as well as provides permutation-invariant penalization of a variable number of outputs per image.

[0039] In the present example, the bipartite matching loss for the pose parsing process may be carried out with the following calculation. The number of predictions from the transformer network may be assumed to be N, where N is preset to a number typically much larger than the maximum number of persons expected in an image. Continuing with this example, y may be the set of ground truth persons and $\hat{y}=\{\hat{y}_t\}_{i=1}^{N}$ may be the set of N predictions. Without loss of generality, y may be considered to also be a set of size N, padded with Ø (no person). To find a bipartite matching between these two sets, a permutation of N elements $\sigma \epsilon S_N$ with the lowest cost may be searched:

$$\hat{\sigma} = \underset{\sigma \in S_N}{\operatorname{argmin}} \sum L_{match}\left(y_i, \hat{y}_{\sigma(i)}\right)$$

where L is a pairwise matching cost between ground truth y_i, and a prediction with an index σ(i). The optimal assignment may be computed with the Hungarian algorithm.

[0040] The matching cost takes into account both a binary class prediction (person/no person) and the similarity of predicted and ground truth poses. Each element i of the ground truth can be seen as $y_i=(c_i, r_i)$ where c, is the target class label and $r_i \epsilon R^{2J}$ is a vector that defines on-image coordinates for the ground truth keypoints comprising a person's pose.

[0041] For the prediction with index σ(i), the probability of class c_i, can be defined as $p\hat{}_{\sigma(i)}(c_i)$ and the predicted pose as $r\hat{}_i$. With these notations, the following may be defined:

$$L_{match}\,(y_i,\hat{y}_{\sigma(i)})\text{as}-1_{\{c_i\neq\emptyset\}}\hat{p}_{\hat{\sigma}(i)}(c_i)+1_{\{c_i\neq\emptyset\}}L_{pose}(r_i,\hat{r}_{\hat{\sigma}(i)}).$$

[0042] The second step is to compute the loss function, the Hungarian loss for all pairs matched in the previous step. The loss is defined by a linear combination of a negative log-likelihood for class prediction and a pose regression loss.

$$L_{Hungarian}(y, \hat{y}) = \sum_{i=1}^{N}\left[-\log \hat{p}_{\hat{\sigma}(i)}(c_i) + 1_{c_1=\varnothing} L_{pose}\left(r_i, \hat{r}_{\hat{\sigma}(i)}\right)\right].$$

[0043] where $\sigma\hat{}$ is the optimal assignment computed in the first step.

[0044] Finally, the pose regression loss is defined as:

$$L_{pose}(r_i,\hat{r}_{\sigma(i)})=\|r_i-\hat{r}_{\sigma(i)}\|2.$$

[0045] The particular form of the pose regression loss may take on other forms, as long as it represents a differentiable function that provides a measure of how different a given pair of poses are.

[0046] Referring to FIG. **5**, a schematic representation of a computer network system is shown generally at **200**. It is to be understood that the system **200** is purely exemplary and it will be apparent to those skilled in the art that a variety of computer network systems are contemplated. The system **200** includes the apparatus **50** to estimate poses of multiple objects from a two-dimensional image, a plurality of external sources **20-1** and **20-2** (generically, these external sources are referred to herein as "external source **20**" and collectively they are referred to as "external sources **20**"), and a plurality of content requesters **25-1** and **25-2** (generically, these content requesters are referred to herein as "content requesters **25**" and collectively they are referred to as "content requesters **25**") connected by a network **210**. The network **210** is not particularly limited and may include any type of network such as the Internet, an intranet or a local area network, a mobile network, or a combination of any of these types of networks. In some examples, the network **210** may also include a peer to peer network.

[0047] In the present example, the external sources **20** may be any type of computing device used to communicate with the apparatus **50** over the network **210** for providing raw data such as an image **100** of an object. For example, the external source **20-1** may be a smartphone. It is to be appreciated by a person of skill with the benefit of this description that the external source **20-1** may be substituted with a laptop computer, a portable electronic device, a gaming device, a mobile computing device, a portable computing device, a tablet computing device or the like. In some examples, the external source **20-2** may be a camera to capture an image. The raw data may be generated from an image or video received or captured at the external source **20**. The content requesters **25** may also be any type of computing device used to communicate with the apparatus **50** over the network **210** to receive the parsed pose estimates of the image **100**. For example, content requesters **25** may be a downstream service provider, such as an animation engine or pose analyzer.

[0048] Referring to FIG. **6**, a flowchart of an example method of to estimate poses of multiple objects from a two-dimensional image is generally shown at **300**. In order to assist in the explanation of method **300**, it will be assumed that method **300** may be performed by the apparatus **50**. Indeed, the method **200** may be one way in which the apparatus **50** may be configured. Furthermore, the following discussion of method **300** may lead to a further understanding of the apparatus **50** and it components. In addition, it is to be emphasized, that method **300** may not be performed in the exact sequence as shown, and various blocks may be performed in parallel rather than in sequence, or in a different sequence altogether.

[0049] Beginning at block **310**, the apparatus **50** receives raw data from an external source via the communications interface **55**. In the present example, the raw data includes a representation of an image with multiple objects, such as people. The manner by which the person is represented and the exact format of the two-dimensional image is not particularly limited. For example, the two-dimensional image may be an RGB format. In other examples, the two-dimensional image be in a different format, such as a raster graphic file or a compressed image file captured and processed by a camera. Once received at the apparatus **50**, the raw data is to be stored in the memory storage unit **60** at block **320**.

[0050] Block **330** involves detects parts of the objects in the image represented by the raw data using the neural network engine **65**, which may apply a convolutional neural network to the raw data. The types of parts of the image detected is not particularly limited. For example, the neural network engine **65** may detect keypoints, such as joints. In other examples, the neural network engine **65** may detect connectors between keypoints, such as bones.

[0051] Next, block **340** comprises generating intermediate representations of the parts that are detected with the neural network engine **65**. The intermediate representation is not particularly limited. For example, the intermediate representation may be a plurality of keypoint heatmaps, where each keypoint heatmap represents a keypoint of one of the objects in the image **100**. In other examples, the intermediate representation may be a plurality of connector heatmaps or associative embeddings.

[0052] A transformer neural network model is applied to the intermediate representation at block **350** to parse the intermediate representations into separate poses of the objects in the image **100** in a differentiable and end-to-end trainable manner. Block **360** uses the parsed intermediate representations to generate a plurality of estimated poses corresponding to the objects in the image.

[0053] Various advantages will now become apparent to a person of skill in the art. In particular, the apparatus **50** may be used to parse poses in a two-dimensional image with an efficient transformer neural network. In particular, this avoids the use of a slow non-differentiable clustering approach and/or other computationally heavy, sequential operations to provide faster processing times. Due to the faster processing times, the process may be carried out on a single graphics processing unit or on a portable electronic device, such as a smartphone. Since many portable electronic devices include a camera, it is to be appreciated by a person of skill in the art with the benefit of this description that the entire process from the capture of an image with multiple objects, such as a sport scene with people, can be processed to generate a plurality of poses for the objects in the image. This may be used by downstream services, such as a pose analyzer, to extract further data or to analyze movements of players in a game or to review errors for improvement by coaching staff.

[0054] It should be recognized that features and aspects of the various examples provided above may be combined into further examples that also fall within the scope of the present disclosure.

I/We claim:

1. An apparatus comprising:

a communications interface configured to receive raw video data from an external source, wherein the raw video data includes a representation of a first person and a second person;

a memory storage unit in which to store the raw video data;

a first neural network engine configured to detect parts of the first person and the second person and to generate an intermediate representation of the parts; and

a second neural network engine to apply a transformer neural network to the intermediate representation to parse the parts into first person parts and second person parts to (i) generate a first pose of the first person from the first person parts and (ii) generate a second pose of the second person from the second person parts.

2. The apparatus of claim **1**, wherein the first neural network engine is to apply a convolutional neural network to the raw video data.

3. The apparatus of claim **2**, wherein the intermediate representation includes a plurality of keypoint heatmaps, each of which represents a keypoint of the first person or the second person, and wherein the plurality of keypoint heatmaps collectively show all visible keypoints of the first person and the second person in the representation.

4. The apparatus of claim **2**, wherein the intermediate representation includes a plurality of affinity fields, each of which is representative of a vector that describes association between the parts.

5. The apparatus of claim **2**, wherein the intermediate representation includes a plurality of associative embeddings, each of which includes a unique identifier that serves to identify each pixel with the first person or the second person.

6. The apparatus of claim **1**, wherein the first neural network engine and the second neural network engine are executed by a graphics processing unit.

7. The apparatus of claim **1**, wherein the second neural network engine is to execute a bipartite matching loss operation to parse the parts of the first object and the second object.

8. A method for establishing poses of first and second objects included in an image, the method comprising:

receiving, via a communications interface, raw data that includes the image of a first object and a second object;

detecting, with a first neural network, parts of the first object and the second object;

generating an intermediate representation of the parts;

applying a second neural network to the intermediate representation to parse the parts into first object parts and second object parts;

generating a first pose of the first object from the first object parts; and

generating a second pose of the second object from the second object parts.

9. The method of claim **8**, wherein generating the intermediate representation comprises generating a plurality of keypoint heatmaps.

10. The method of claim **8**, wherein generating the intermediate representation comprises generating a plurality of affinity fields.

11. The method of claim **8**, wherein generating the intermediate representation comprises generating a plurality of associative embeddings.

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

executing a neural network engine that applies the second neural network on a graphics processing unit.

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

executing a bipartite matching loss operation to parse the parts into the first object parts and the second object parts.

14. A non-transitory computer readable medium encoded with codes, wherein the codes are to direct a processor to:

receive raw data that includes a representation of a first object and a second object;

detect parts of the first object and the second object by applying a convolutional neural network to the raw data;

generate an intermediate representation of the parts;

apply a transformer neural network to the intermediate representation to parse the parts into first object parts and second object parts;

generate a first pose of the first object from the first object parts; and

generate a second pose of the second object from the second object parts.

15. The non-transitory computer readable medium of claim **14**, wherein the codes are to direct the processor to generate a plurality of keypoint heatmaps as a portion of the intermediate representation.

16. The non-transitory computer readable medium of claim **14**, wherein the codes are to direct the processor to generate a plurality of affinity fields as a portion of the intermediate representation.

17. The non-transitory computer readable medium of claim **14**, wherein the codes are to direct the processor to generate a plurality of associative embeddings as a portion of the intermediate representation.

18. The non-transitory computer readable medium of claim **14**, wherein the codes are to direct the processor to apply the transformer neural network on a graphics processing unit.

19. The non-transitory computer readable medium of claim **14**, wherein the codes are to direct the processor to execute a bipartite matching loss operation to parse the parts into first object parts and second object parts.

20. A method for establishing poses of multiple persons included in an image, the method comprising:

applying, to the image, a first neural network that identifies parts of the multiple persons;

generating an intermediate representation of the parts;

applying, to the intermediate representation, a second neural network that parses the parts into multiple sets, each of which is associated with a corresponding one of the multiple persons; and

for each of the multiple persons, generating a pose based on the corresponding set of the multiple sets.

* * * * *