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(54) **ASSISTED LABELLING OF TRAINING DATA FOR MACHINE LEARNING MODELS**

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B60W 60/00 (2020.01)
(Continued)

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CPC B60W 60/0027; B60W 2554/4044; B60W 2554/4041; B60W 2554/4042;
(Continued)

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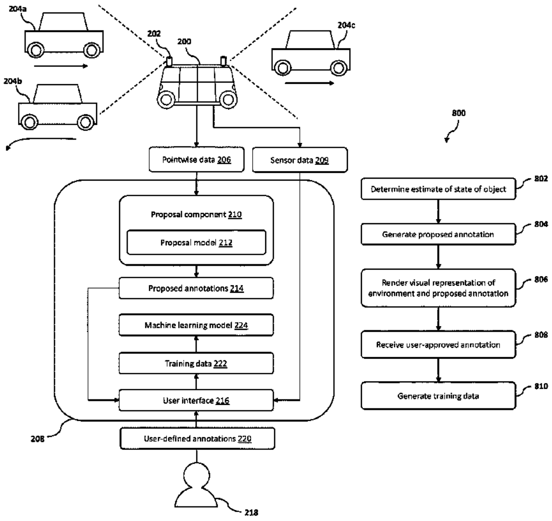
(57) **ABSTRACT**

A computer-implemented method. Includes determining an estimate of a state of an object detected at a first time step, based on a pointwise estimate of the state of the object at the first time step and pointwise measurements of the state of the object at a plurality of further time steps. Includes generating, using the estimate of the state of the object, a proposed annotation associated with the object at the first time step. Includes rendering, via a user interface, a visual representation of the environment at the first time step and a visual representation of the proposed annotation. Includes receiving, via the user interface, user input indicating a user-approved annotation associated with the object at the first time step. Includes generating training data for a machine learning model for use in controlling an autonomous vehicle, based at least in part on the user-approved annotation.

20 Claims, 8 Drawing Sheets


204a
202
200
204c
204b
800
Pointwise data 206
Sensor data 209
802
Determine estimate of state of object
Proposal component 210
Proposal model 212
804
Generate proposed annotation
Proposed annotations 214
806
Render visual representation of environment and proposed annotation
Machine learning model 224
Training data 222
808
Receive user-approved annotation
User interface 216
810
Generate training data
208
User-defined annotations 220
218

(51) **Int. Cl.**

G05B 13/02	(2006.01)
G06T 7/20	(2017.01)
G06T 7/70	(2017.01)
G06V 10/764	(2022.01)
G06V 10/94	(2022.01)
G06V 20/58	(2022.01)
G06V 20/70	(2022.01)

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

CPC ***G06T 7/20*** (2013.01); ***G06T 7/70*** (2017.01); ***G06V 10/764*** (2022.01); ***G06V 10/945*** (2022.01); ***G06V 20/58*** (2022.01); ***G06V 20/70*** (2022.01); *B60W 2540/215* (2020.02); *B60W 2554/4041* (2020.02); *B60W 2554/4042* (2020.02); *B60W 2554/4043* (2020.02); *B60W 2554/4044* (2020.02); *G06T 2200/24* (2013.01); *G06T 2207/20081* (2013.01); *G06T 2207/30252* (2013.01)

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See application file for complete search history.

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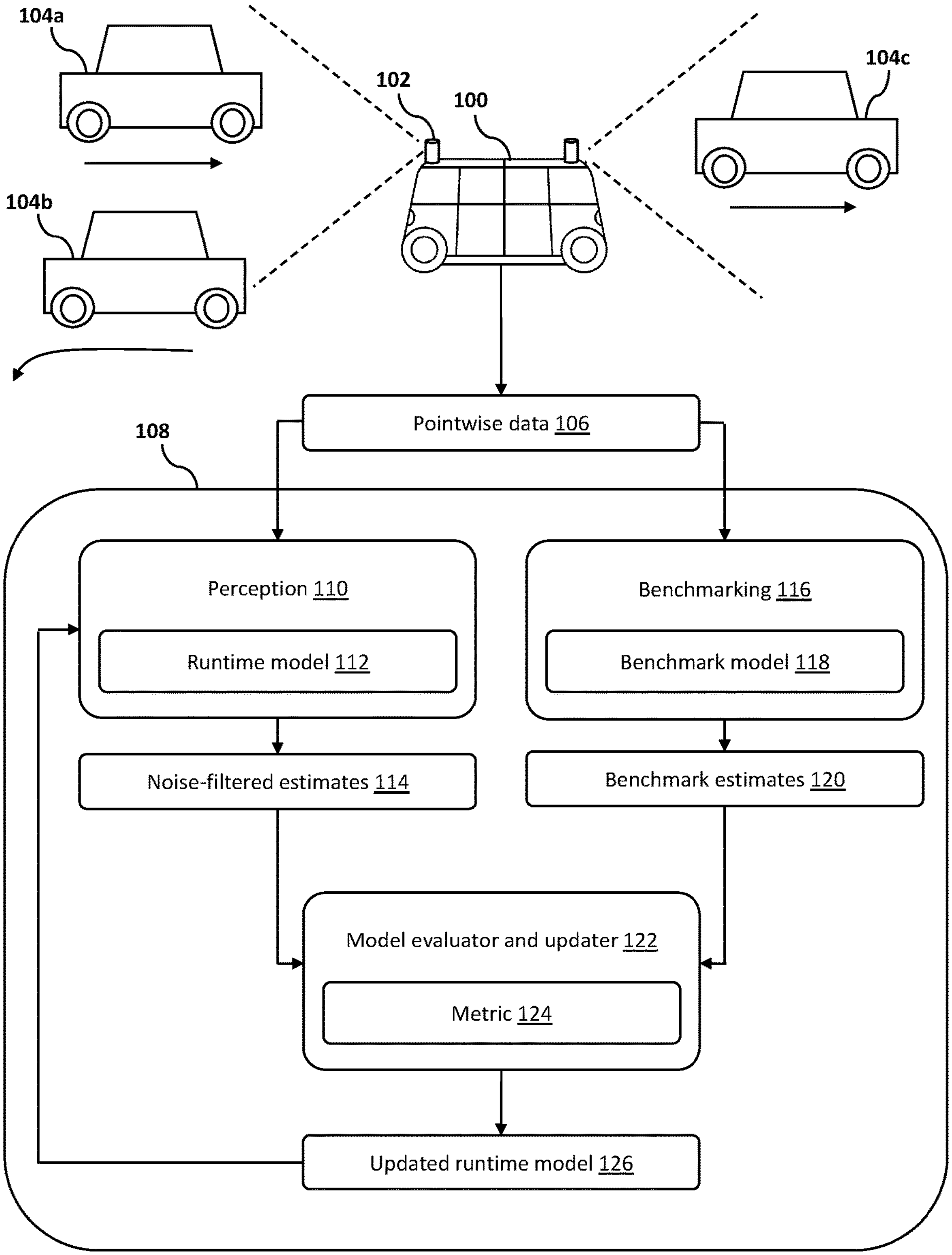
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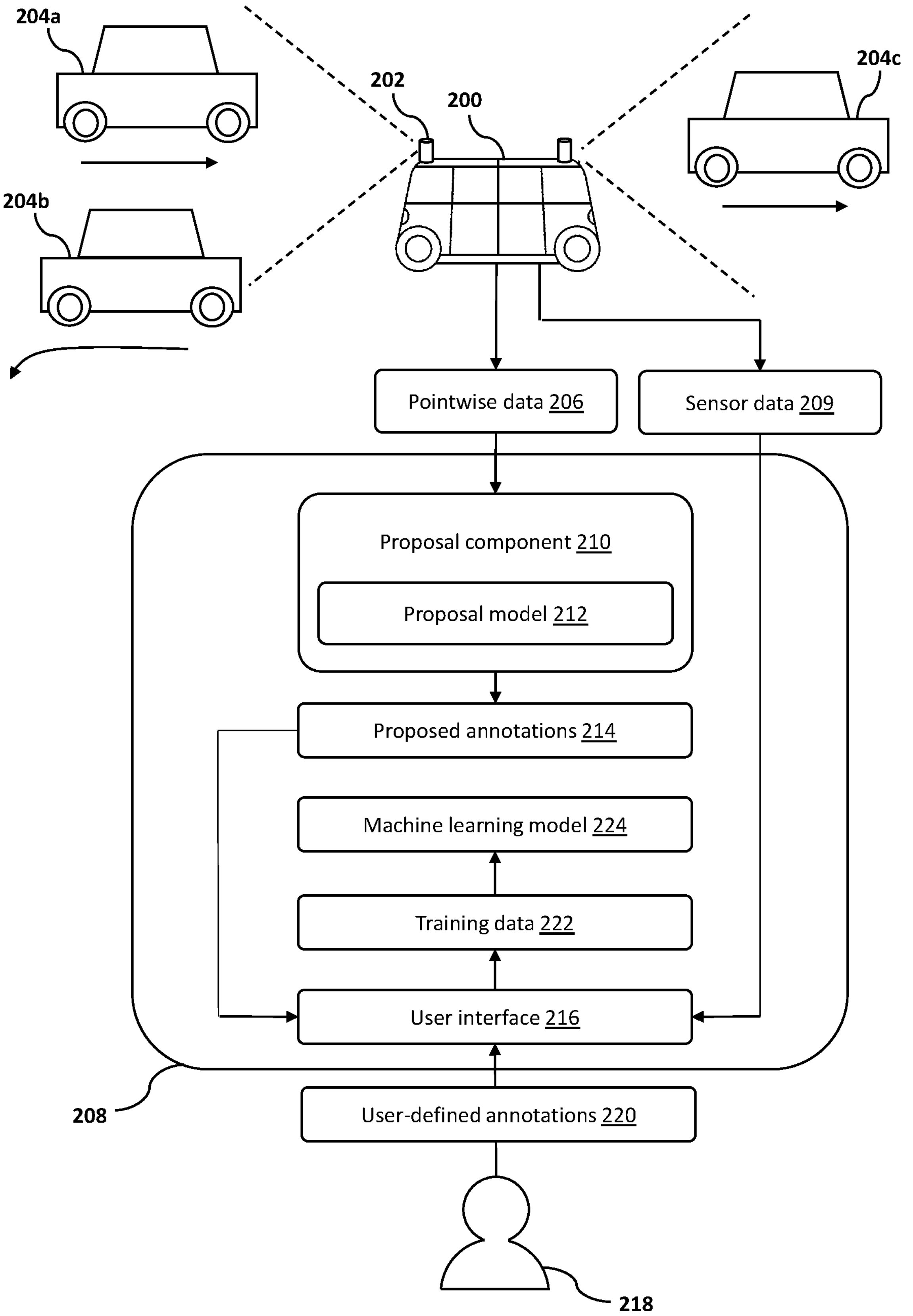
100
104c
Pointwise data 106
108
Perception 110
Runtime model 112
Benchmarking 116
Benchmark model 118
Noise-filtered estimates 114
Benchmark estimates 120
Model evaluator and updater 122
Metric 124
Updated runtime model 126

FIG. 1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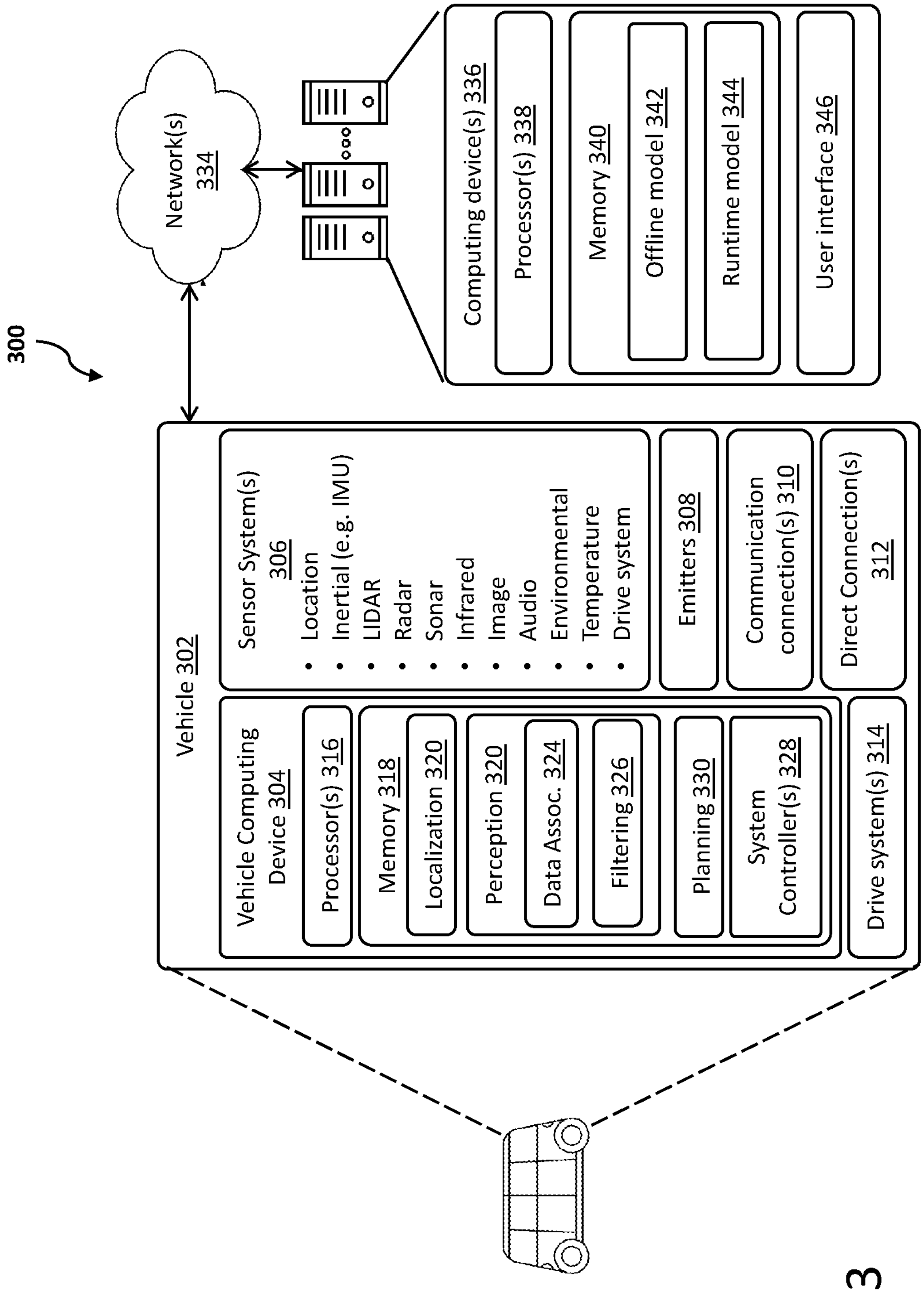
204c
Pointwise data 206
Sensor data 209
Proposal component 210
Proposal model 212
Proposed annotations 214
Machine learning model 224
Training data 222
User interface 216
208
User-defined annotations 220
218

FIG. 2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Vehicle 302
Vehicle Computing Device 304
Processor(s) 316
Memory 318
Localization 320
Perception 320
Data Assoc. 324
Filtering 326
Planning 330
System Controller(s) 328
Drive system(s) 314
Sensor System(s) 306
• Location
• Inertial (e.g. IMU)
• LIDAR
• Radar
• Sonar
• Infrared
• Image
• Audio
• Environmental
• Temperature
• Drive system
Emitters 308
Communication connection(s) 310
Direct Connection(s) 312
Network(s) 334
Computing device(s) 336
Processor(s) 338
Memory 340
Offline model 342
Runtime model 344
User interface 346

FIG. 3

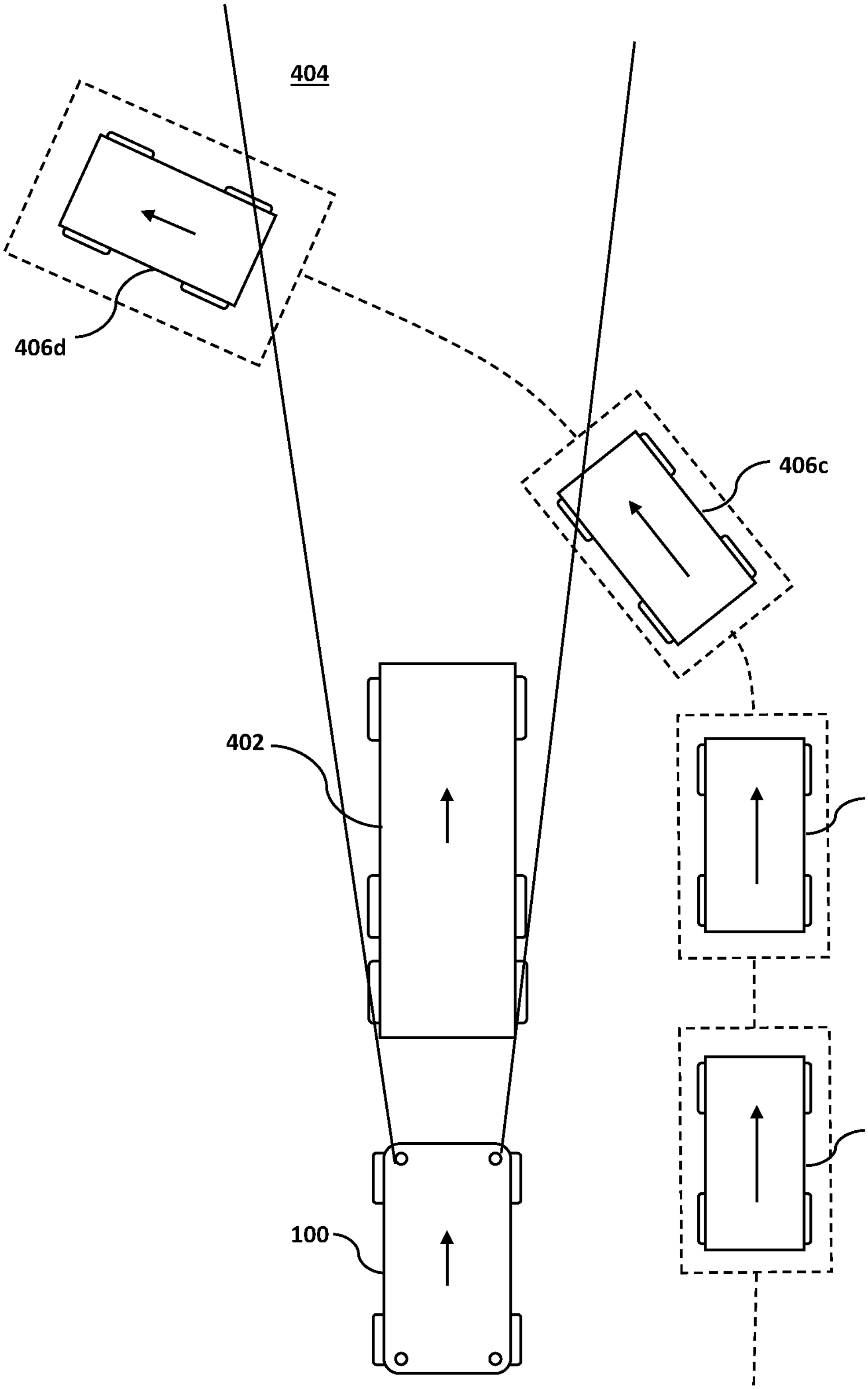


FIG. 4

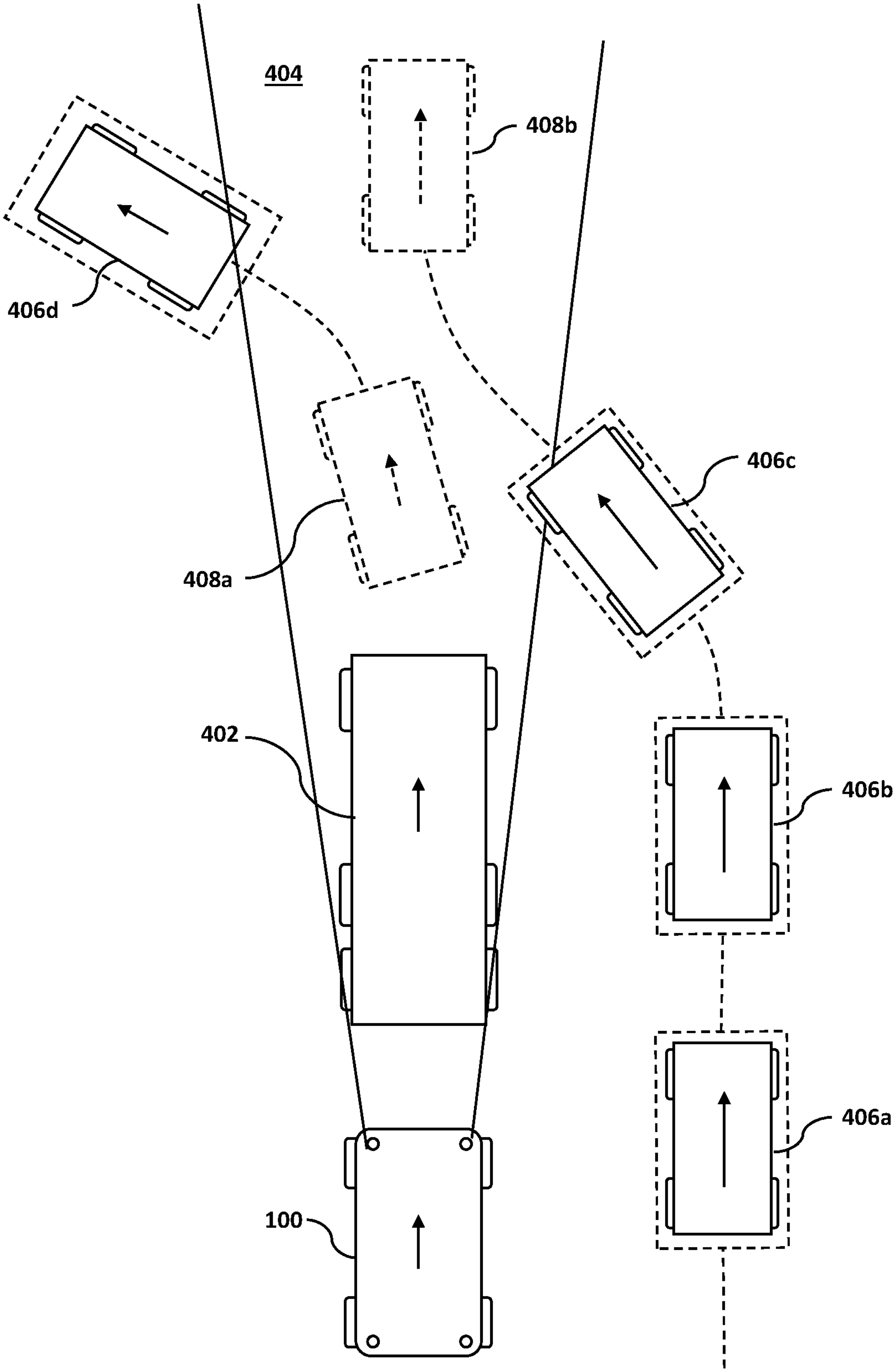
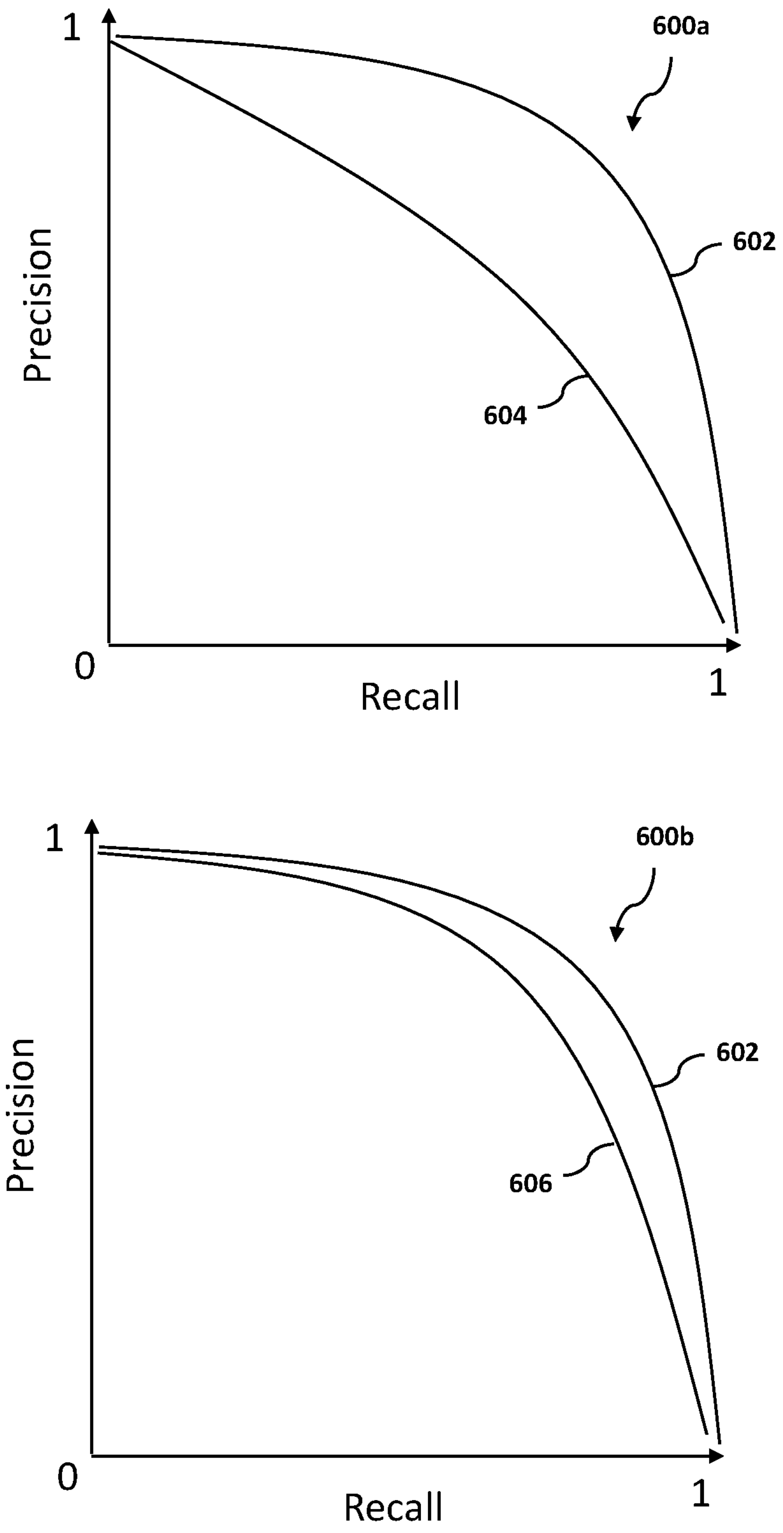


FIG. 5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600b
Precision
602
606
0
Recall
1

FIG. 6

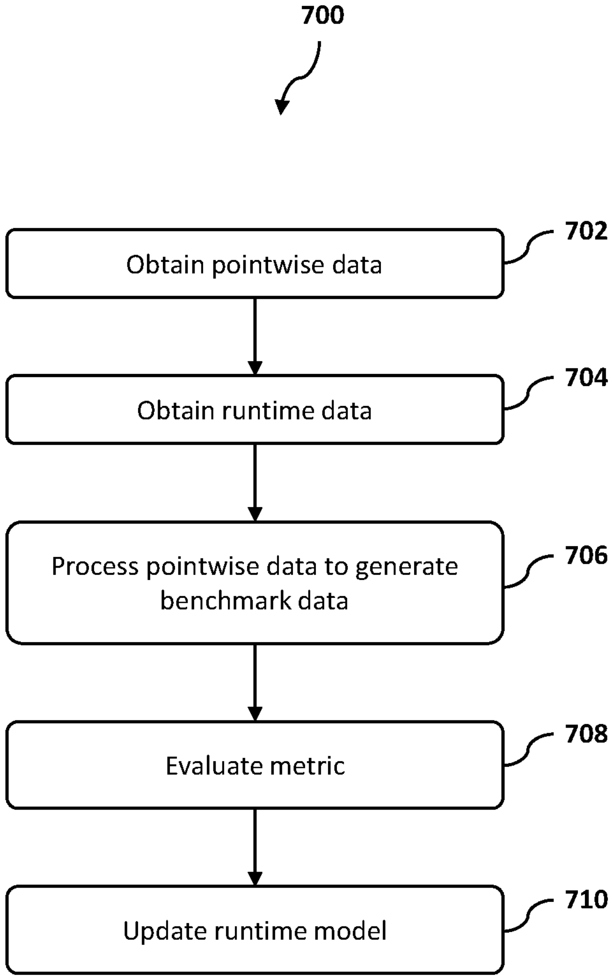
700
Obtain pointwise data
702
Obtain runtime data
704
Process pointwise data to generate benchmark data
706
Evaluate metric
708
Update runtime model
710

FIG. 7

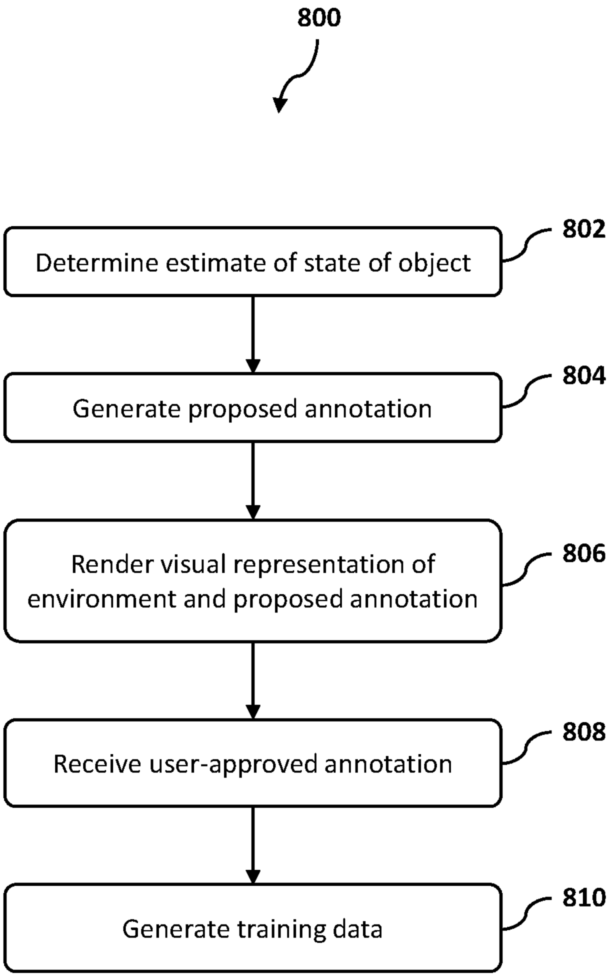
800
Determine estimate of state of object
802
Generate proposed annotation
804
Render visual representation of environment and proposed annotation
806
Receive user-approved annotation
808
Generate training data
810

FIG. 8

ASSISTED LABELLING OF TRAINING DATA FOR MACHINE LEARNING MODELS

BACKGROUND

An autonomous vehicle typically includes a range of sensors and an onboard data processing system capable of detecting entities, such as other vehicles, in its vicinity, and estimating kinematic variables associated with those entities, such as position, orientation and velocity. By tracking an individual entity, information derived from earlier estimations of its kinematic variables may be used to refine a current estimation of its kinematic variables.

BRIEF DESCRIPTION OF DRAWINGS

The detailed description is described with reference to the accompanying figures. The use of the same reference numbers in different figures indicates similar or identical components or features.

FIG. **1** is a schematic diagram of a system for benchmarking a runtime system for deployment on a vehicle.

FIG. **2** is a schematic diagram of a system for assisted labelling of training data for a machine learning model.

FIG. **3** depicts a block diagram of an example system for implementing the techniques described herein.

FIG. **4** illustrates a first tracking hypothesis for entities in a vicinity of an autonomous vehicle.

FIG. **5** illustrates a second tracking hypothesis for entities in a vicinity of an autonomous vehicle.

FIG. **6** depicts precision and recall curves for a runtime model and a benchmark model before and after the inference system is updated in accordance with examples.

FIG. **7** depicts a flowchart representing a method of benchmarking a runtime model, in accordance with examples.

FIG. **8** depicts a flowchart representing a method of annotating data for training a machine learning model, in accordance with examples.

DETAILED DESCRIPTION

The present disclosure relates to methods and systems for estimating states of entities, such as dynamic entities in a vicinity of an autonomous vehicle. In this context, dynamic entities (sometimes referred to as agents) may include vehicles or other objects capable of movement within an environment, and may be distinguished from static objects within the environment by virtue of their capability of movement. A state of an entity refers to one or more properties associated with the entity at a given point in time. The state may include dynamic properties which are expected to vary over time, including values of one or more kinematic variables such as the position and/or orientation of the entity, along with time derivatives of these quantities, such as velocity and/or rate of rotation. Alternatively, or additionally, the state of an entity may include static properties which are expected to remain constant over time, including geometric properties of the entity such as dimensions, extent, and/or shape of the entity. The state of an entity may be represented as vector with components representing respective state variables. In the context of an entity in the vicinity of an autonomous vehicle, the vector may for example represent planar (horizontal) position, planar velocity, yaw and yaw rate. Other variables may additionally, or alternatively, be included in the state, such as vertical position, pitch, or roll, along with their associated time derivatives.

An autonomous vehicle may include one or more sensors and an object detection system for detecting entities in the vicinity of the autonomous vehicle. The autonomous vehicle may further include an onboard perception component configured to estimate a state of a detected entity using sensor data collected from the one or more sensors at a given point in time or within a narrow temporal window (such as a few milliseconds) around a given point in time. An estimate of a state derived from data associated with a given point in time may be referred to as a pointwise measurement of the state.

A pointwise measurement of a state can be subject to various sources of error and noise, including observation noise caused by inherent uncertainties associated with the sensor(s), occlusion error caused by an entity being wholly or partly blocked from one or more sensors, and kinematic noise caused by unpredictable motion of the sensor(s) such as vibrations caused by an uneven road surface. The effect of such errors on a pointwise measurement of a state can be mitigated using information derived from estimates of one or more earlier states. In particular, by tracking an individual entity over time, a noise filter can be applied recursively to the pointwise measurements of the states of the entity at a series of time steps to determined runtime estimates of the states, which may mitigate at least some of the sources of error that can affect the pointwise measurements. In order to facilitate this, the onboard perception component of the autonomous vehicle may include a data association model to associate instances of entities detected at different time steps, along with a noise filter.

Prior to deployment of a data association model and/or a noise filter, values of associated parameters of the data association model and/or noise filter may be determined based on physical considerations (for example, based on kinematic equations of motion and/or known uncertainties associated with one or more sensors), or based on empirical data. For example, values of the associated parameters may be determined using online or offline machine learning methods. A difficulty of the latter approach is that ground truth states of entities observed in an environment are rarely available, except where simulations are used, but such simulations may not accurately represent the various sources of noise and errors present in a real physical environment. More generally, ground truth data can be difficult to obtain for machine learning tasks relevant to the control of an autonomous vehicle, due to the highly time-consuming and resource-intensive process of labelling data covering a sufficiently diverse range of scenarios.

In view of the above issues, the present disclosure provides an offline tool arranged to process pointwise measurements of states of entities detected over a period of time to determine offline estimates of the states of those entities. The offline estimates may be determined using an offline model and may more accurately represent the true states of the entities than the runtime estimates determined using the runtime model. The offline estimates may therefore be treated as pseudo-ground truth values of the states, in situations where a sufficient volume/diversity of ground truth data is not readily available.

In contrast with the runtime model, the offline model of the present disclosure may not be suitable for execution in an online setting, for example onboard an autonomous vehicle. In particular, to determine an offline estimate of a state of an entity at a given time step, the offline model may be configured to use information from time steps later than the given time step. This is in contrast with the runtime model, which may only use information from earlier time steps. A model that requires information from future time steps will necessarily operate with a temporal lag, and this may be undesirable in the context of a runtime model in an autonomous vehicle or other setting where decisions need to be made with minimal delay. Furthermore, execution of the offline model may require significantly more processing than execution of the runtime model, which may introduce an unacceptable level of lag and/or prevent the offline model from being executable in real time or near-real time. In some cases, the computational cost of executing the offline model may be prohibitively high for execution by a computer system onboard an autonomous vehicle.

Examples of noise filters suitable for implementation onboard an autonomous vehicle may include Kalman-type filters (such as a Kalman filter, extended Kalman filter, or unscented Kalman filter), though other filters such as particle filters and Gaussian process-based filters may be employed additionally or as an alternative. In this way, a pointwise measurement of a state may be refined based on information derived from the pointwise measurement of the previous state (and, optionally, one or more earlier states), resulting in various types of noise being filtered out from the measurement, providing that the noise can reasonably be modelled as uncorrelated from one time step to the next. Further refinement is possible using such a filter in combination with a robust loss function, which makes the output of the noise filter less sensitive to outliers.

In order for a noise filter to be applied to a given sequence of pointwise measurements, instances of entities detected at different time steps may first be associated with one or more "tracks" using a data association model, and the noise filter may be applied to instances associated with a common track. An entity associated with a track using the data association model may be referred to a track entity or a track object. The data association model aims to correctly associate instances of the same entity at different time steps with a common track. If an instance of an entity cannot be associated with an existing track (for example because the entity has only just come into range of the sensors and/or object detection system), then the data association model may create a new track, or may reject the instance as a false detection. In a multi-entity or multi-agent setting (as is typical in a driving environment), the data association task may not have a unique solution. For example, if an entity becomes occluded for one or more time steps, it may be difficult to determine whether a later detection corresponds to the same entity or an entirely new entity. In order to determine whether to associate an instance of an entity detected at a given time step with an existing track or whether to initiate a new track, the data association model may use estimates of states from previous time steps. For example, the mean and covariance of a noise-filtered estimate from a previous time step may be used to define a "gated" region of state space in which a new measurement may be determined to correspond to the same entity. Further criteria may be introduced to resolve ambiguities for example where multiple measurements appear in the gated region of state space. Such criteria may for example use classification and/or bounding box loss to resolve such ambiguities. Examples of data association models include network flow-based models, Markov Chain Monte Carlo (MCMC) data association, joint probabilistic data association, and multidimensional assignment.

As mentioned above, the combination of a data association model and a filtering model may be implemented in combination as a runtime (or "online") model, for example to be executed by computing hardware onboard an autonomous vehicle. The runtime model may be configured to processes pointwise measurements of states of entities detected in the vicinity of the autonomous vehicle to generate runtime estimates of the states of the entities, which may be used to predict trajectories of the entities and to plan which actions, if any, should be taken by the autonomous vehicle in dependence on the predicted trajectories of the entities. The runtime model thereby enables the autonomous vehicle to take actions which are less adversely affected by noise than if the pointwise measurements were used directly.

The performance of the data association model and the filtering model (collectively referred to as the runtime model) may be affected by values of a number of associated parameters. For example, the data association model may include parameters for controlling whether a new track is created for a given detection of an entity (as opposed to classifying as a false detection), and/or for controlling if a detected entity is associated with an existing track. The filtering model may include parameters characterizing various type(s) of noise/error associated with the pointwise measurements. In the case of a Kalman-type filter, a pointwise measurement z_t of a state at a given time step t may be modelled as a noisy observation of the true state x_t at that time step t such that $z_t=g(x_t)+v_t$, where g is a measurement operator and v_t is a measurement noise which captures random errors associated with the measurement of the state. The state x_t at time step t is assumed to be derivable from the state x_{t-1} at a previous time step t−1 by application of a linear or nonlinear state transition operator f, such that the operator f represents the time evolution of the state. In some examples, at least some components of the state, such as the dimensions of the entity, are not expected to change over time, whereas other components, such as the position of the entity, may change over time. The time evolution of the state is assumed to be subject to state transition noise w_t which captures random (uncorrelated) variations in the system dynamics, such that $x_t=f(x_{t-1})+w_t$. Depending on the filtering model, the operators f and/or g may each have known parametric forms (for example based on known equations of motion), in which case the parameters of the operators f and/or g may be parameters of the runtime model. Alternatively, the operators f and/or g may be modelled in a nonparametric fashion, for example being governed by latent Gaussian processes, in which case hyperparameters of the latent Gaussian processes may be parameters of the runtime model. The measurement noise v_t and the state transition noise w_t may be modelled as Gaussian noise parameterized by respective covariance matrices, in which case the entries of these covariance matrices may also be parameters of the runtime model.

The state transition operator f may depend on the classification of the entity, reflecting the fact that different entities may be subject to different dynamics. For example, a vehicle with four-wheel steering may be able to move in a direction that is different from the direction the vehicle is facing (e.g. drift), whereas a vehicle with two-wheel steering may only be able to move in the direction the vehicle is facing (unless conditions are identified which may cause the vehicle to lose traction with the road).

Whereas the runtime model described above may include a noise filter, the offline model of the present disclosure may include a smoother, such as a Rauch-Tung-Striebel (RTS) smoother, a two-filter smoother, a sequential importance resampling smoother, a Rao-Blackwellized particle smoother, or a grid-based smoother. For a given noise filter (such as a Kalman-type filter), an associated smoother may be constructed by applying recursion in a reverse temporal direction to update and improve estimates from the filtering model. In this way, using information from future time steps may drastically reduce the uncertainty of an estimate for a given time step. By incorporating information from future time steps, certain hypotheses regarding the state can be ruled out. The smoother may be a fixed-lag smoother configured to estimate the state of an entity a predetermined number of time steps before the latest available time step. Alternatively, the smoother may be a fixed-point smoother configured to estimate a state of the entity at a fixed time step, using the information from an increasing number of future time steps. Alternatively, the smoother may be a fixed-interval smoother configured to estimate states of an entity over a fixed interval, given pointwise measurements of the states of the entity over the same interval. The smoother may be an optimal smoother in the Bayesian sense (aka Bayes optimal), meaning that for a given filtering model the smoother may determine the most likely value of the state at each time step, given the information available to the smoother. Optimal smoothing equations are available for all Kalman-type filters, and may be evaluated using a series of recursive calculations in the reverse temporal direction. Effectively, a smoother may take information captured at a sequence of time steps and solve a Bayesian optimization problem to provide the most likely configuration of states over that sequence of time steps (in other words, the joint distribution of states having the highest likelihood). In an offline setting, parameters associated with the smoother (such as entries of the covariance matrices associated with the measurement noise v_t and the state transition noise w_t) may be optimized or learned from the data, either for individual tracks or globally for all tracks in a given time frame, resulting in smoothed estimates of the states which may be Bayes optimal with respect to the chosen filtering model.

The smoother may be a Gaussian process-based smoother. A smoother of this kind may be associated with a Gaussian process-based filter and may not assume a parametric form of the underlying state transition operator f and measurement operator g, but instead may associate each of these operators with one or more Gaussian processes whose posterior distributions are determined using Bayesian inference. For certain Gaussian process models, exact inference may be performed, enabling a joint posterior distribution for the states and their uncertainties over a sequence of time steps to be determined in closed form. Alternatively, approximate inference may be used, for example using sampling techniques or sparse approximations of the underlying Gaussian processes. In either case, hyperparameters of the Gaussian processes may be optimized using maximum a posteriori (MAP) estimation, maximum likelihood estimation, evidence maximization, or sampling. Gaussian process inference, including hyperparameter optimization, may be highly computationally expensive and unsuitable for use in an online setting.

The offline model may include a multiple hypotheses batch tracking model. Over a sequence of time steps, a multiple hypotheses tracking model may be configured to construct and update so-called track trees encapsulating one or more tracking hypotheses. A track tree may have nodes corresponding to detections of one or more entities at each of a sequence of time steps, and branches that connect detections on hypothetical tracks (or trajectories) between time steps. At a given time step, a new track tree may be constructed for each entity detected at that time step, accounting for the possibility that the detection corresponds to a new entity coming into detection range. Existing track trees may also be updated with detections from the given time step. In particular, an existing track tree may be extended by appending as separate branches any new detections consistent with an existing node in the track tree. A new detection at a given time step may be considered to be consistent with an existing node in the track tree if the pointwise measurement of its state (or simply its position or another subset of state variables) is within a predetermined metric distance D (for example, a predetermined Mahalanobis distance) of the state (or subset of the state) predicted for that time step according to a filtering model applied at the existing node, or in other words if the measurement falls within a region of state space depending on the noise-filtered estimate of the state at the previous time step. An additional branch may be appended to the track tree to account for occlusion or an otherwise missing detection of an entity at a given time step.

Track trees may be pruned at some or all time steps according to one or more pruning criteria, and the track hypotheses remaining after pruning may be scored, for example in dependence on their Bayesian likelihoods as derived from the filtering model and/or other factors such as bounding box loss and/or classification loss. After pruning, the configuration of track hypotheses (i.e. global hypothesis) having a highest overall score may be determined by solving a discrete optimization problem (such as a maximum weighted independent set (MWIS) optimization problem), and the determined configuration may be identified as the correct global hypothesis at the given time step, such that each track in the identified global hypothesis may be determined to correspond to multiple instances of a common entity.

In an online setting, multiple hypotheses tracking models are constrained by the need to rapidly prune track trees to prevent exponential growth of the number of track hypotheses, as well as the fact that the model can only use information from previous time steps. Either or both of these constraints may result in the true track configuration being missed, particularly if parameters for the tracking model are not tuned correctly. Pruning may be performed using a range of techniques, for example N-scan pruning in which branches corresponding to the global hypothesis at time step k are traced backward to the corresponding nodes at time step k-N (for a predetermined parameter value N), and subtrees diverging from the from the global hypothesis at that node are removed. In this way, branches of a track tree which are distant from the global hypothesis are removed. In effect, ambiguities in data association up to time step k-N are resolved by looking ahead for a window of N frames. Other examples of pruning criteria include pruning track trees that have more than a predetermined value B of branches, for example by keeping only the B highest scoring branches. In an online setting, the values of the parameters D, B and/or N (and possibly other parameters depending on the data association model) may be chosen to satisfy a trade-off between accuracy and computational cost. For example, selecting larger values of D, B, and/or N reduces the probability of missing a true global hypothesis, but increases the computational cost and running time of the data association model. Therefore, online settings may be limited to using relatively small values for these parameters, which may limit the practicality of the multiple hypotheses tracking model for use in online settings.

In the present setting, the offline model may utilize a multiple hypothesis tracking model (or any other suitable type of tracking model) in an offline manner. As explained above, the offline model is not restricted to using information from past time steps, and temporal lag may not be a primary consideration as may be the case for an online model. The lifting of these restrictions may enable the use of parameter values which result in a highly accurate data association model (for example high values of D, B and/or N for the multiple hypotheses batch tracking model described above). Furthermore, the data association model may be run in forward and/or reverse temporal direction, which may further improve accuracy. In a particular example, a smoother (such as one of the smoothers discussed above) may be run for each candidate track at each time step, resulting in a more accurate estimate of the Bayesian likelihood and more accurate determination of the correct track configuration. In other examples, the offline model may forego the use of track trees entirely, and for example perform an exhaustive search over track configurations within a fixed temporal horizon. Although the number of track configurations may increase exponentially with the size of the temporal horizon, limiting the size of the temporal horizon may enable all track configurations to be considered in a reasonable timescale for the offline setting. In this example, a smoother may be applied to each track in each candidate track configuration, enabling an accurate Bayesian likelihood to be determined for each track for the purpose of data association. Such a method may be applied for example using a sliding temporal window.

By using a Bayes optimal smoother and an accurate data association model, such as a multiple hypotheses batch tracking model, the offline model may be capable of generating a globally Bayes optimal set of estimates of the states of entities detected in a given time frame. Such estimates may be treated as pseudo-ground truth values for the states, for example in settings when ground truth data is unavailable or insufficient for a given task.

To expand on the above, FIG. **1** illustrates an example in which an offline model as described above is used to generate pseudo-ground truth data for benchmarking a runtime model for deployment on an autonomous vehicle. FIG. **1** shows an autonomous vehicle **100** having an onboard perception component (not shown) configured to process data captured by onboard sensors **102** to detect and classify entities in the vicinity of the vehicle, and to estimate the states of the detected entities. In this example, three dynamic entities **104***a*, **104***b*, **104***c* (collectively referred to as entities **104**) are detected in the vicinity of the vehicle **100** and classified as vehicles, and the onboard perception component determines pointwise measurements of the states of the entities **104** at a sequence of time steps for which the entities **104** are in range of the sensors **102** (including position, velocity, yaw and yaw rate, represented by the arrows below the entities **104**). The onboard perception system is further configured to process the pointwise measurements using a runtime model as discussed above to determine runtime estimates of the states of the entities **104**. These runtime estimates are passed to an onboard prediction component and an onboard planning component, which together determine actions to be performed by a drive system of the vehicle **100**. It is to be noted that the onboard perception component is for determining states of objects or entities other than the vehicle **100**. The vehicle **100** may further include a localization component, which by contrast is for determining a position and/or orientation of the vehicle **100** itself.

During operation, the onboard perception component of the vehicle **100** can generate pointwise data **106** indicating the pointwise measurements of the states of the entities **104** at different time steps. The pointwise data **106** may further include metadata relevant to the downstream processing of the pointwise measurements, such as timestamps and classifications for the entities **104**. The pointwise data **106** may be stored in any suitable format by one or more memory devices onboard the vehicle **100**, for example in log files and/or relational databases. Optionally, the unprocessed sensor data from which the pointwise measurements are derived may also be stored in association with the pointwise data **106**. In the present example, the vehicle **100** provides the pointwise data **106** to a remote system **108**, for example by transmission over a network (not shown) using wired and/or wireless communication means. The pointwise data **106** may be provided to the remote system **108** in a streaming fashion or in batches, either periodically (such as every hour, day, week etc.) or when certain conditions are satisfied, such as when a suitable wired or wireless connection to the network is available and/or when a certain volume of pointwise data **106** has been generated. The vehicle **100** may additionally or alternatively provide the unprocessed sensor data, and/or the runtime estimates determined using the runtime model, to the remote system **108**.

The remote system **108** includes an offline perception component **110**, which has similar functionality to the onboard perception component of the vehicle **100**. The offline perception component **110** includes a runtime model **112**. Although the runtime model **112** is stored and executed on the remote system **108**, the runtime model **112** may be suitable to be stored and executed onboard a vehicle such as the autonomous vehicle **100**. The runtime model **112** may be an instance of the same runtime model stored onboard the vehicle **100**, or may differ from the runtime model stored onboard the vehicle **100**, for example by having different parameter values and/or by implementing a different data association model and/or filtering model.

The offline perception component **110** may be configured to process the pointwise data **106** received from the vehicle **100**, along with pointwise data received from (possibly many) other vehicles, using the runtime model **112**, to generate runtime estimates **114** of the states of entities detected by those vehicles. The runtime model **112** may be configured to associate a given instance of an entity detected at a given time step with a further instance detected at an earlier time step, in accordance with a data association model. The runtime model **112** may be configured to filter the pointwise measurement of the state associated with the given instance in dependence on a runtime estimate of the state associated with the further instance at the earlier time step, in accordance with a filtering model. In this way, the runtime model iteratively generates the runtime estimates **114** of the states of detected entities, using information which is available in a runtime setting (i.e. without using information from future time steps). It is to be noted that in some examples, the offline perception component **110** may be omitted and the runtime estimates **114** may be received directly from one or more vehicles with perception components running instances of a common runtime model.

The remote system **108** further includes a benchmarking component **116**. The benchmarking component **116** may be configured to process the pointwise data **106** received from the vehicle **100**, along with pointwise data received from (possibly many) other vehicles, using a benchmark model **118**, to generate benchmark estimates **120** of the states of entities detected by those vehicles. The benchmark model **118** may include an offline data association model and a smoother, for example as described above, and accordingly may be capable of generating more accurate estimates of the states of entities than the runtime model **112**. In particular, the benchmark model **118** may use information from future time steps to determine a benchmark estimate at a given time step. Furthermore, in some cases the benchmark model **118** may arrive at a different track hypothesis to the runtime model **112**, as illustrated in an example below.

FIG. **4** shows a top-down view of a scene involving the autonomous vehicle **100**. In this scene, the autonomous vehicle **100** is driving behind a bus **402** such that there is an occluded region **404** of the scene which is hidden from at least some of the sensors on the vehicle **100** (as shown between the solid lines in FIG. **4**). Using the sensors **102** and the onboard data processing system, the autonomous vehicle **100** detects instances of an entity classified as a "car" a set of time steps t_a, t_b, t_c, t_d (whose positions relative to the autonomous vehicle **100** are simultaneously shown in FIG. **4** as instances **406***a*, **406***b*, **406***c*, **406***d*, **406***e*). in this example, the interval between each pair of adjacent times steps is equal, apart from the interval between t_c and t_d, which is twice as long as there was no detection of an entity (other than the bus **402**) at an intervening time step. At each of the time steps t_a, t_b, t_c, t_d, the autonomous vehicle **100** determines a pointwise measurement of the state associated with the instance detected at that time step. Pointwise data **106** indicating the pointwise measurements at time steps t_a, t_b, t_c, t_d are transmitted to the remote system **108**.

The offline perception component **110** processes the pointwise data **106** using the runtime model **112** to determine runtime estimates of the states associated with the instances **406***a*, **406***b*, **406***c*, **406***d* detected at the time steps t_a, t_b, t_c, t_d. As explained above, the runtime model **112** includes a data association model and a filtering model. In this example, the data association model associates each of the instances **406***a*, **406***b*, **406***c*, **406***d* with a common track (as indicated by dashed curves), corresponding to the hypothesis that all of the instances **406***a*, **406***b*, **406***c*, **406***d* are instances of the same car. The uncertainty in the filtered estimates of the states are represented by the dashed bounding boxes around the instances **406***a*, **406***b*, **406***c*, **406***d*. It is observed that the uncertainty in the states associated with the instances **406***a*, **406***b*, **406***c* is relatively low, whereas the uncertainty in the state associated with the instance **406***d* is higher, because a greater interval has elapsed since the previous time step and uncertainty under the filtering model grows with time between measurements.

The benchmarking component **116** processes the pointwise data **106** using the benchmark model **118** to determine benchmark estimates of the states associated with the instances **406***a*, **406***b*, **406***c*, **406***d* detected at the time steps t_a, t_b, t_c, t_d. As shown in FIG. **5**, the benchmark model associates each of the instances **406***a*, **406***b*, **406***c* with a common track, but initiates a new track for the instance **406***d*, corresponding to the hypothesis that the instance **406***d* is a different car to the instances **406***a*, **406***b*, **406***c*. In this case, the hypothesis of the benchmark model **118** corresponds to the ground truth, whereas the hypothesis of the runtime model **112** is incorrect (dashed instances **408***a*, **408***b* show the ground truth positions of the two cars at time steps when the two cars are occluded). It is further observed that the uncertainties in the states associated with the instances are consistently lower for the benchmark model **118** than for the runtime model **112**, even for the instance **406***d* for which a new track is initiated. The benchmark model **118** is able to correctly resolve tracking ambiguities, and to determine more accurate estimates of states, at least in part because the benchmark model **118** is able to leverage information from future time steps, whereas the runtime model is constrained to using information from past time steps. The benchmark model **118** may further use a different data association model to the runtime model **112**.

The offline perception component **110** and the benchmarking component **116** may send the runtime estimates **114** and the benchmark estimates **120** to a model evaluator and updater **122**, optionally with similar data generated from other sources (such as many other autonomous vehicles). The model evaluator and updater **122** is configured to process the runtime estimates **114** and the benchmark estimates **120** to generate data corresponding to an updated runtime model **126**. In particular, the model evaluator and updater **122** may be configured to evaluate a metric **124** measuring a deviation between the runtime estimates **114** and the corresponding benchmark estimates **120** and to update the runtime model **112** in dependence on the evaluation of the metric. By treating the benchmark estimates **120** as pseudo-ground truth, the metric **124** may be used to measure the performance of the runtime model **112**. The performance of the runtime model **112** may be affected by various factors, as described below, and therefore the benchmarking component **116** and the model evaluator and updater **122** may be run separately for different sets of pointwise data **106**, resulting in multiple versions of the updated runtime model **126**.

The runtime model **112** may perform differently in different environmental conditions, for example at different times of day (corresponding to different lighting conditions), in different driving environments (such as urban environments or countryside environments), and/or in different weather conditions. The components of the remote system **108** may therefore be run separately using pointwise data **106** for respective different environmental conditions to generate respective different updated runtime models **126** appropriate for the different environmental conditions. For example, in dark or snowy conditions the measurement noise may be greater, and it may be more difficult for the runtime model **112** to associate an object instance with a given track, in which case different thresholds for object association may be appropriate.

The runtime model **112** may perform differently when used with different perception components or different versions of a perception component. The components of the remote system **108** may be therefore be run separately using pointwise data **106** generated by different perception components or different versions of a perception component, resulting in different updated runtime models **126** appropriate for the respective different perception components of different versions of a perception component. For example, different values of the measurement noise and thresholds for object association may be appropriate depending on the accuracy of the object detection model used in generating the pointwise data **106**.

The metric **124** may measure a pairwise deviation between runtime estimates and benchmark estimates of a state. For example, the metric **124** may depend on a metric distance between a runtime estimate of a state of an entity detected at a given time step and a benchmark estimate of the state of the entity. The metric **124** may for example be a function of the L**1** loss, the smoothed L**1** loss, the L**2** loss, or any other suitable pairwise distance measure. By summing or otherwise combining these losses over multiple detections within a given time period, the metric **124** may measure the performance of the runtime model **112** over that time period. The metric **124** may additionally or alternatively measure a pairwise deviation between uncertainty estimates between runtime estimates and benchmark estimates of a state. For example, for each detection at each time step, a Kalman-type filter (and corresponding smoother) may generate an a posteriori covariance matrix for the state, which may be considered an estimate of the predicted accuracy of the runtime estimate of the state. The metric **124** may then depend on a metric distance between the a posteriori covariance of a runtime estimate and the a posteriori covariance of a corresponding benchmark estimate. By measuring the deviation between the state estimates and the associated uncertainty estimates, the metric **124** may measure the efficacy of the runtime model **112** at filtering out noise in state measurements and also in estimating how much confidence can be attributed to the resulting estimates. In safety-critical environments, such as driving environments, it is important for uncertainty to be quantified as certain actions should only be taken if there is sufficient confidence in the perception of the environment.

As an alternative to measuring pairwise deviations, the metric **124** may measure a deviation between joint probability distributions of the runtime estimates **114** and the benchmark estimates **120**. For example, the metric **124** may depend on a Kullback-Leibler (KL) divergence of a first probability distribution from a second probability distribution, where the first (or second) probability distribution may be the joint probability distribution of runtime estimates (as defined by the runtime estimates and their corresponding posterior covariances), and the second (or first) probability distribution may be the joint probability distribution of the corresponding benchmark estimates. The joint distributions may be taken over multiple detections, optionally over multiple time steps, for example within a given time frame.

As explained above, the runtime model **112** may perform data association less accurately than the benchmark model **118**. A metric **124** which measures the deviation between the runtime estimates **114** and the benchmark estimates **120**, and optionally their corresponding uncertainty estimates, may automatically capture situations where tracking predictions diverge between the runtime model **112** and the benchmark model **118**, because different tracking predictions will result in the noise filtering using information from different earlier states. In the example of FIG. **4**, the runtime estimate of the state associated with the instance **406***d* is derived from the runtime estimate of the state associated with the instance **406***c*. By contrast, the benchmark estimate of the state associated with the instance **406***d* is independent of the state associated with the instance **406***c*. Even if the filtering model is highly accurate, these differing tracking predictions would likely result in differences between the runtime estimates and the benchmark estimates. In this way, the metric **124** may capture deviations between the two data association models in the case of tracking ambiguities. In other cases, it may be preferable for the metric **124** to compare runtime estimates and benchmark estimates only for instances where the same tracking predictions are made. In this way, the metric **124** may measure the accuracy of the filtering model, as opposed to the combined effect of the data association model and the filtering model.

In addition to, or instead of, measuring the deviation between estimates of states, the metric **124** may explicitly measure deviations between tracking predictions made by the runtime model **112** and the benchmark model **118**. For example, the metric **124** may count how many times the runtime model **112** and the benchmark model **118** branch from one another within a given time frame. Alternatively, the data association problem for a given time step may be viewed as a classification problem, for example where each detected instance is classified either as a new entity, a false detection, or an entity which has been seen at a previous time step, in which case the metric **124** may measure precision and recall for this classification problem (treating the output of the benchmark model **118** as ground truth). Alternatively, the metric **124** may measure precision and recall in relation to the cardinality of the set of entities (i.e. the number of entities estimated to be present) over one or more time steps.

The model evaluator and updater **122** is configured to generate data corresponding to an updated runtime model **126** in dependence on the evaluation of the metric **124**. The updated runtime model **126** may depend on evaluations of the metric **124** aggregated over multiple sources of data, for example multiple autonomous vehicles including the vehicle **100**. The model evaluator and updater **122** may for example determine, based on the evaluation of the metric **124**, that one or more aspects of the performance of the runtime model **112** differ from those of the benchmark model **120** by more than a threshold amount, and therefore that the runtime model **112** should be updated. The model evaluator and updater **122** may determine that the data association portion of the runtime model **112** needs to be updated, and/or that the filtering portion of the runtime model **112** needs to be updated. The model evaluator and updater **122** may update the indicated aspect(s) of the runtime model **112**. The updated runtime model **126** may then be evaluated against the benchmark model **118** to determine whether the update was effective at improving the runtime model **112**. The updating of the runtime model **112** may include, for example, replacing the data association model and/or the filtering model with a different data association model and/or filtering model.

The updating of the runtime model **112** may involve updating values of one or more parameters associated with the data association model and/or filtering model. The updating may involve sampling new values for the one or more parameters, using a sampling technique such as random search, grid search, or MCMC sampling. The sampling may be performed iteratively in a manner to optimize the values of the one or more parameters with respect to the evaluation of the metric **124**. For example, the updating may use MCMC sampling in which the sampling distribution is conditioned on the evaluation of the metric **124**. In some examples, Bayesian optimization may be performed, which provides a principled framework for dealing with the exploration/exploitation dilemma encountered when optimizing parameter values. Suitable Bayesian optimization methods may adopt a surrogate function such as a Gaussian process, Bayesian neural network, or other stochastic function or process for predicting the evaluation of the metric **124** for a given set of parameter values, then derive an acquisition function from this surrogate function, for example based on entropy search or expected improvement, and parameter values may then be sampled on the basis of the acquisition function. The acquisition function may be arranged to automatically balance exploration and exploitation (e.g. moving from exploration in the early stages of experimentation towards exploitation in the later stages of experimentation). In other examples, the sampling of parameter values may be performed by a reinforcement learning agent.

Alternatively, or additionally, values of one or more parameters of the runtime model **112** may be optimized using gradient-based optimization, for example using stochastic gradient descent or any of its variants. Gradient-based optimization may be a suitable for situations where the metric **124** is differentiable with respect to one or more parameters of the runtime model **112**.

In some examples, the remote system **108** may have access to ground truth data for tracking and/or states of detected entities. In this case, the model updater **122** may further use the ground truth data for updating the runtime model **112**. For example, the model updater **122** may measure the accuracy of the benchmark model **118** and the accuracy of the runtime model **112** using the ground truth data, enabling the model updater **112** to determine whether inaccuracies in tracking decisions and/or runtime estimates of the states determined by the runtime model **112** are caused by deficiencies in the runtime model **112** (in which case the runtime model **112** is expected to perform significantly worse than the benchmark model **118**) and/or inaccuracies in the pointwise data **106** (in which case the output of the benchmark model **118** is expected to differ significantly from the ground truth).

In the example of FIG. **6**, the upper frame **600***a* shows a first precision and recall curve **602** and a second precision and recall curve **604** for the task of estimating cardinality, where the first curve **602** corresponds to the benchmark model **118** and the second curve **604** corresponds to the runtime model **112**. For both models, the precision and recall are measured against the ground truth and aggregated from multiple data sources. It is observed that the area under the second curve **604** is significantly lower than the area under the first curve **602**, indicating that the benchmark model **118** outperforms the runtime model **112** in this task. In this example, the model updater **122** updates parameter values of the runtime model **112** in dependence on a comparison between the first precision and recall curve **602** and the second precision and recall curve **604**. For example, the model updater **112** may perform MCMC sampling, where the sampling distribution is conditioned on a difference between the first precision and recall curve **602** and the second precision and recall curve **604**, for example a difference between the areas of the curves. The lower frame **600***b* of FIG. **6** shows the first precision and recall curve **602** and a third precision and recall curve **606**, where the third curve **606** corresponds to the updated runtime model **112**. It is observed that the third curve **606** is closer than the second curve **604** to the first curve **602**, indicating that the runtime model **112** has improved as a result of the updating.

Although the system **108** is described above as being remote from the vehicle **100**, in other examples a vehicle may have an onboard component for implementing the benchmark model and for generating update data for updating the runtime model on the vehicle. This may enable a vehicle to adapt its own runtime model based on data generated in its own environment, though may not benefit from data generated by other vehicles.

FIG. **7** shows an example of a computer-implemented method **700**, which may be implemented by a computing system such as the remote system **108** of FIG. **1**. The method **700** includes obtaining, at **702**, pointwise data indicating, for a plurality of time steps, a pointwise measurement of a state of an object detected by an object detection system. The object may for example be an object in a vicinity of an autonomous vehicle or other type of vehicle. The object detection system may be part of a perception component onboard the vehicle, in which case the pointwise data may be received from the perception component onboard the vehicle. Alternatively, the pointwise data may be determined remotely from the vehicle, for example by processing raw sensor data or log data received from the vehicle.

The method **700** proceeds by obtaining, at **704**, runtime data indicating, for the plurality of time steps, a runtime estimate of the state of the object. The runtime data is generated by a runtime model, which may be implemented as part of a perception system onboard a vehicle, or may be implemented remotely from a vehicle. The runtime data may be generated by processing the pointwise data recursively, as described elsewhere in the present disclosure. The runtime model may for example include an online data association model and a filtering model.

The method **700** proceeds by processing, at **706**, the pointwise data to determine, for the plurality of time steps, a benchmark estimate of the state of the object. The benchmark data is generated by a benchmark model, which may be an offline system remote from the source of the pointwise data. The benchmark model may include determining the benchmark estimate of the state of the object at a given time step based on the pointwise measurement of the state of the object at the given time step and at a plurality of further time steps, the plurality of further time steps including at least one time step later than the given time step. In this way at least, the benchmark model may contrast with the runtime model. The benchmark model may for example include an offline data association model and a smoother.

The method **700** proceeds by evaluating, at **708**, a metric measuring, for the plurality of time steps, a deviation between the runtime estimate and the benchmark estimate of the state of the object.

The method **700** concludes by updating, at **710**, the runtime model, based on the evaluation of the metric. The updated runtime model may optionally be used to generate further runtime data, such that the method **700** returns to **704** and continues iteratively until a stopping condition is satisfied, for example a convergence condition or a predetermined number of iterations having been performed.

As a further illustration, FIG. **2** shows an example in which an offline model as described above is used for assisted labelling of data, for example to be used as labelled training data for a machine learning model. Examples of techniques for assisted labelling of data can be found, for example, in U.S. patent application Ser. No. 17/538,909, filed Nov. 30, 2021, and titled “Generating and Training Object Detection Models for Autonomous Vehicles”, the contents of which are incorporated by reference herein, in their entirety for all purposes.

FIG. **2** shows an autonomous vehicle **200** with sensors **202** for detecting and determining pointwise measurements of the states of dynamic entities, including vehicles **204***a*, **204***b*, **204***c*. The autonomous vehicle **200** in FIG. **2** may be functionally identical to the autonomous vehicle **100** in FIG. **1**, and is similarly arranged to transmit pointwise data **206** to a remote system **208**. The pointwise data **206** indicates pointwise measurements of the states of entities detected in the vicinity of the autonomous vehicle **200** at different time steps. In this example, the vehicle **200** further provides sensor data **209** captured by the onboard sensors **202** to the remote system **208**. The sensor data **209** may be raw and/or processed sensor data and includes data from which a visual representation of the environment surrounding the vehicle **200** can be derived. Although in the present example the vehicle **200** provides the pointwise data **206** to the remote system **208**, in other examples the remote system **208** may instead derive the pointwise data **206** from the sensor data **209**.

The sensor data **209** may include sufficient input (test) data for a machine learning model (such as a neural network model) arranged to perform object detection and/or other tasks relevant to controlling an autonomous vehicle, including but not limited to semantic segmentation, instance segmentation, object classification, and object tracking.

Machine learning models for these purposes are typically trained using supervised learning based on labelled training data. The process of obtaining such labelled training data covering a sufficiently diverse range of scenarios can be highly time-consuming and resource-intensive and conventionally involves a human user manually applying labels or annotations. Labels are metadata associated with an input data item (such as an image) which may be compared with the output of a machine learning model during supervised learning. In this context, labels may include, for example, bounding boxes, bounding contours for semantic segmentation or instance segmentation, class labels, tracking predictions, and so on, for certain types of entities identified in the input data item.

To assist with the data labelling process, the remote system **208** includes a proposal component **210** configured to process the pointwise data **206** using a proposal model **212** to generate proposed annotations **214** for the sensor data **209**. The proposal model **212** may include an offline data association model and a smoother, for example as described above, and accordingly may determine refined estimates of the states associated with instances detected at a given time step, based on accurate tracking predictions. The proposal model **212** may further include a trained machine learning model and/or heuristic model for performing a task such as object detection and/or other tasks relevant to controlling an autonomous vehicle. The proposed annotations **214** may depend on the tracking predictions and/or the refined estimates of the states. For example, the proposal model **212** may be arranged to determine a common class label for instances of entities associated with a common track, based on confidence levels associated with class labels for instances on the track. In this way, a common class label may propagate along the track, even where the confidence levels are low for some instances (for example in the case of partial occlusion). On the other hand, a change in class label on a predicted track may cause the proposal model **212** to re-evaluate the tracking prediction, as described above with regard to resolving tracking ambiguities. More generally, the proposal model **212** may be arranged to enforce or encourage continuity of proposed annotations on a given track, for example by ensuring that bounding boxes or bounding contours associated with different instances of an entity do not imply a change in size or shape of the entity. In another example, the proposal model **212** may be arranged to determine a position and/or orientation of a detected instance, based on the refined estimates of the states associated with instances on the same track. This may enable, for example, accurate top-down bounding boxes to be determined for all instances on the track. In this way, the proposal model **212** may use information from multiple instances associated with a common track to determine proposed annotations which are accurate and robust against noise.

The remote system **208** includes a user interface **216**, which may include a combination of hardware and software components to enable a user **218** to interact with the remote system **208**. The user interface **216** may include one or more displays, one or more input devices, along with associated rendering software and drivers for these devices. The user interface **216** is arranged to render a visual representation of the environment derived from the sensor data **209**, for example an image or video representing the environment at one or more time steps, to be viewed by a user **218**. The visual representation may be an image-based representation based on image data captured by the sensors **202** (e.g., cameras). In other examples, the visual representation may include a non-image based visual representation, such as a visual representation of a lidar point cloud, a radar or sonar return signal, or the like. In some cases, the user interface **216** may present one or more visual representations based on a combination of different sensor modalities of the same environment, such as a visual image and a corresponding lidar point cloud, etc. The visual representation may be rendered from the perspective of the vehicle, and/or from various other angles, such as a top-down view of the environment.

The user interface **216** is further arranged to render a visual representation of one or more proposed annotations **214**, for example overlaid on the visual representation of the environment. The visual representation of the proposed annotation(s) **214** may include one or more of a proposed bounding box, a proposed bounding contour for semantic segmentation or instance segmentation, and/or text or symbols indicating a proposed class label for an entity. The user interface **216** may further enable the user **218** to modify the proposed annotation(s) **214** or otherwise provide user-approved annotation(s) **220** using the one or more input devices, having been presented the proposed annotation(s) **214**. For example, the user interface **216** may render a visual representation of a proposed class label for a detected object, and provide means for the user **218** to either approve the class label or reject the class label. In the case that the user **218** rejects the class label, the user interface **216** may present alternative class labels (for example, in order of decreasing confidence as determined by the proposal model **212**). The user **218** may then select a user-approved class label from the list of alternative class labels. In another example, the user interface **216** may present multiple options for proposed annotation (for example, multiple proposed class labels), and may enable the user **216** to select one of the proposed annotations, in which case the selected annotation may become the user-approved annotation. In another example, the visual representation of the proposed annotation may include a proposed bounding box, for example a bounding box for an entity as viewed from the perspective of the vehicle **200**, or a top-down bounding box (e.g. if the visual representation of the environment is a top-down representation). In case the user **218** determines that the proposal model **212** has inaccurately determined the size, shape, and/or location of the entity, the user interface **216** may allow the user to drag the corners of the bounding box to new positions, thereby to determine a user-approved bounding box to correspond more accurately to the boundaries of the entity. Alternatively, the user interface **216** may allow the user to draw or otherwise define a new user-approved bounding box, having viewed the proposed bounding box. In the case the user **218** determines that a proposed annotation corresponds to a false detection, the user interface **216** may enable the user to delete the proposed annotation.

In response to receiving a user-approved annotation which differs from a proposed annotation relating to the same instance of an entity, the proposal component **210** may be configured to update proposed annotations for one or more further instances detected at respective different time steps. For example, the user **218** may specify a class label for a given instance detected at a given time step. The given instance may be associated with a track having a sequence of further instances, in accordance with the data association model. The proposal component **210** may therefore update the proposed class label of any instances associated with the same track to match the class label specified by the user **218**. The user **218** may subsequently be presented with a visual representation of the environment at a later or earlier time step, along with the updated proposed class label for instances on the track. The updating of proposed annotations in this way may be dependent on confidence values associated with the original and/or updated class label for the further instances. For example, if the original and updated class labels for one of the further instances are assigned similar confidence levels, the proposal component **210** may perform the update as described, whereas if the original class label has a significantly higher confidence level than the updated class label for the further instance, then the proposal component **210** may refrain from performing the update. The proposal component **210** may be configured to update bounding boxes, bounding contours, or other proposed annotations in a similar fashion. For example, if the user **218** modifies the size and/or shape of a bounding box or contour for a given instance, the proposal component **210** may modify the size and/or shape of a bounding box or contour commensurately for a further instance on the same track.

The user interface **216** may be arranged to present a video stream representation of the environment over a sequence of time steps, along with corresponding annotations. The user **218** may be provided with means to pause or rewind the video stream to a chosen time step in order to provide user-approved annotations for that time step. Once an annotation has been corrected at a given time step, the correction may propagate to other instances associated with the same track, as explained above, providing an intuitive and time-efficient method for the user to correct annotations over several time steps.

The remote system **208** generates labelled training data **222** based at least in part on the user-approved annotations **220** and the sensor data **209**. The labelled training data **220** may further include proposed annotations **214** that have been explicitly or implicitly accepted by the user **218**. The remote system **208** may use the labelled training data **222** for supervised training of a machine learning model **224**. The machine learning model **224** may be suitable for use in controlling an autonomous vehicle, and may be the same or different to the machine learning model implemented by the proposal model **212** to generate the proposed annotations **214**. The machine learning model **224** may for example be a runtime model suitable for usage onboard an autonomous vehicle. As an offline model, the proposal model **212** may be capable of performing a given task more accurately than the runtime machine learning model **224**. The combination of proposed annotations **214** generated by the proposal model **212** and user-approved annotations **220** provided by the user **218** may therefore represent a sufficiently good approximation of ground truth data for effective training of the machine learning model **224**.

The machine learning model **224** may be trained using labelled training data aggregated from multiple sources, for example based on sensor data received from many autonomous vehicles. Furthermore, the task of generating user-approved annotations may be shared between many users accessing the remote system **208**, or using other systems, for example in exchange for financial remuneration. The methods and techniques described herein may vastly increase the speed and accuracy with which labelled training data can be generated.

FIG. **8** shows an example of a computer-implemented method **800**, which may be implemented by a computing system such as the remote system **208** of FIG. **2**. The method **800** includes determining, at **802**, an estimate of a state of an object at a first time step, based on a pointwise measurement of the state of the object at the first time step and pointwise measurements of the state of the object at a plurality of further time steps. The estimate of the state may be determined using an offline model as described herein, for example including a data association model and a smoother.

The method **800** proceeds by generating, at **804**, a proposed annotation associated with the object at the first time step. The proposed annotation may be generated using the estimate of the state of the object determined at **802**.

The method **800** proceeds by rendering, at **806**, via a user interface, a visual representation of an environment containing the object at the first time step and a visual representation of the proposed annotation. The visual representation of the environment and the pointwise measurement of the state of the object at the first time step may derived from common sensor data.

The method **800** proceeds by receiving, at **808**, user input via the user interface, user input indicating a user-approved annotation associated with the object at the first time step. As explained above, the user-approved annotation may be an approval or confirmation of the proposed annotation, or may be a modified annotation which differs from the proposed annotation.

The method **800** concludes by generating, at **810**, training data for a machine learning model for use in controlling an autonomous vehicle, based at least in part on the user-approved annotation. The training data may include an input portion (such as an image) based on sensor data from which the pointwise measurement of the state of the object at the first time step is derived, and a label based on the user-approved annotation.

FIG. **3** depicts a block diagram of an example system **300** for implementing the techniques described herein. In some instances, the system **300** may include a vehicle **302**, which may correspond to the vehicle **100** of FIG. **1**, and/or the vehicle **200** of FIG. **2**. In some instances, the vehicle **302** may be an autonomous vehicle configured to operate according to a Level **5** classification issued by the U.S. National Highway Traffic Safety Administration, which describes a vehicle capable of performing all safety-critical functions for the entire trip, with the driver (or occupant) not being expected to control the vehicle at any time. However, in other examples, the autonomous vehicle **302** may be a fully or partially autonomous vehicle having any other level or classification. Moreover, in some instances, the techniques described herein may be usable by non-autonomous vehicles as well.

The vehicle **302** can include vehicle computing device(s) **304**, one or more sensor systems **306**, one or more emitters **308**, one or more communication connections **310**, at least one direct connection **312** (e.g., for physically coupling the vehicle **302** to exchange data and/or to provide power), and one or more drive systems **314**.

In some instances, the sensor(s) **306** may include light detection and ranging (LIDAR) sensors, RADAR sensors, ultrasonic transducers, sonar sensors, location sensors (e.g., global positioning system (GPS), compass, etc.), inertial sensors (e.g., inertial measurement units (IMUs), accelerometers, magnetometers, gyroscopes, etc.), cameras (e.g., red-green-blue (RGB), infrared (IR), intensity, depth, time of flight, etc.), microphones, wheel encoders, environment sensors (e.g., temperature sensors, humidity sensors, light sensors, pressure sensors, etc.), etc. The sensor(s) **808** may include multiple instances of each of these or other types of sensors. For instance, the LIDAR sensors may include individual LIDAR sensors located at the corners, front, back, sides, and/or top of the vehicle **302**. As another example, the cameras may include multiple cameras disposed at various locations about the exterior and/or interior of the vehicle **302**. The sensor(s) **306** may provide input to the vehicle computing device(s) **304**.

The vehicle **302** may also include the emitter(s) **308** for emitting light and/or sound, as described above. The emitter(s) **308** in this example may include interior audio and visual emitter(s) to communicate with passengers of the vehicle **302**. By way of example and not limitation, interior emitter(s) may include speakers, lights, signs, display screens, touch screens, haptic emitter(s) (e.g., vibration and/or force feedback), mechanical actuators (e.g., seatbelt tensioners, seat positioners, headrest positioners, etc.), and the like. The emitter(s) **308** in this example may also include exterior emitter(s). By way of example and not limitation, the exterior emitter(s) in this example include lights to signal a direction of travel or other indicator of vehicle action (e.g., indicator lights, signs, light arrays, etc.), and one or more audio emitter(s) (e.g., speakers, speaker arrays, horns, etc.) to audibly communicate with pedestrians or other nearby vehicles, one or more of which comprising acoustic beam steering technology.

The vehicle **302** may also include the communication connection(s) **310** that enable communication between the vehicle **302** and one or more other local or remote computing device(s). For instance, the communication connection(s) **310** may facilitate communication with other local computing device(s) on the vehicle **302** and/or the drive system(s) **314**. Also, the communication connection(s) **310** may additionally or alternatively allow the vehicle **302** to communicate with other nearby computing device(s) (e.g., other nearby vehicles, traffic signals, etc.). The communication connection(s) **310** may additionally or alternatively enable the vehicle **302** to communicate with a computing device **336**.

The vehicle computing device(s) **304** can include one or more processors **316** and memory **318** communicatively coupled with the one or more processors **316**. In the illustrated example, the memory **318** of the vehicle computing device(s) **304** stores a localization component **320**, an onboard perception component **322** including a data association model **324** and a filtering model **326**, one or more system controllers **328**, and a planning component **330**. Though depicted in FIG. **3** as residing in memory **318** for illustrative purposes, it is contemplated that the localization component **320**, the perception component **322**, the one or more system controllers **328**, and/or the planning component **330** may additionally, or alternatively, be accessible to the vehicle **302** (e.g., stored remotely).

In some instances, the perception component **322** can include functionality to perform object detection, semantic segmentation, instance segmentation, and/or classification. In some examples, the perception component **322** can generate processed sensor data that indicates a presence of an entity that is proximate to the vehicle **302** and/or a classification of the entity as an entity type (e.g., car, pedestrian, cyclist, animal, building, tree, road surface, curb, sidewalk, unknown, etc.). In additional or alternative examples, the perception component **322** can provide processed sensor data that indicates one or more characteristics associated with a detected entity (e.g., a tracked object) and/or the environment in which the entity is positioned. In some examples, characteristics associated with an entity can include, but are not limited to, an x-position (global and/or local position), a y-position (global and/or local position), a z-position (global and/or local position), an orientation (e.g., a roll, pitch, yaw), an entity type (e.g., a classification), a velocity of the entity, an acceleration of the entity, an extent of the entity (size), etc. Characteristics associated with the environment can include, but are not limited to, a presence of another entity in the environment, a state of another entity in the environment, a time of day, a day of a week, a season, a weather condition, an indication of darkness/light, etc.

In at least one example, the vehicle computing device(s) **304** can include one or more system controllers **328**, which can be configured to control steering, propulsion, braking, safety, emitters, communication, and other systems of the vehicle **302**. The system controller(s) **328** can communicate with and/or control corresponding systems of the drive system(s) **314** and/or other components of the vehicle **302**.

The system controller(s) **328** may be communicatively coupled to one or more sensors of the vehicle sensor system(s) **306**. By way of non-limiting example, the sensors may detect the presence of objects in the environment of the vehicle and/or determine attributes of those objects. The system controller(s) **328** may also cause activation of a safety system of the vehicle **302** when it is determined that the safety system should be activated. For example, the system controller(s) **328** may instruct an airbag control unit to deploy one or more airbags, or may send a signal to a tensioner arranged to adjust tensioning of one or more restraints. Other safety systems are known and may be activated. In other embodiments, the system controller **328** may instruct activation of multiple safety systems. In some embodiments, some or all functionality of the system controller **328** may be performed remote from the vehicle **302**, e.g., at a remote server associated with a dispatch or headquarters for the vehicle **302** or in the cloud. In other implementations, some or all of the functionality of the system controller(s) **328** may be performed at the vehicle **302** to minimize any delay that could result from the transmission of data between locales.

The drive system(s) **314** may include many of the vehicle systems, including a high voltage battery, a motor to propel the vehicle, an inverter to convert direct current from the battery into alternating current for use by other vehicle systems, a steering system including a steering motor and steering rack (which may be electric), a braking system including hydraulic or electric actuators, a suspension system including hydraulic and/or pneumatic components, a stability control system for distributing brake forces to mitigate loss of traction and maintain control, an HVAC system, lighting (e.g., lighting such as head/tail lights to illuminate an exterior surrounding of the vehicle), and one or more other systems (e.g., cooling system, safety systems, onboard charging system, other electrical components such as a DC/DC converter, a high voltage junction, a high voltage cable, charging system, charge port, etc.). Additionally, the drive system(s) **314** may include a drive system controller which may receive and preprocess data from the sensor(s) and to control operation of the various vehicle systems. In some instances, the drive system controller may include one or more processors and memory communicatively coupled with the one or more processors. The memory may store one or more modules to perform various functionalities of the drive system(s) **314**. Furthermore, the drive system(s) **314** may also include one or more communication connection(s) that enable communication by the respective drive system with one or more other local or remote computing device(s).

In some examples, the vehicle **302** can send operational data, including raw or processed sensor data from the sensor system(s) **306**, to one or more computing device(s) **336** via the network(s) **334**. In other examples, the vehicle **302** can send processed operational data and/or representations of operational data to the computing device(s) **336** at a particular frequency, after a lapse of a predetermined period of time, in near real-time, etc. In some cases, the vehicle **302** can send raw or processed operational data to the computing device(s) **336** as one or more log files.

The one or more computing device(s) **336** can include one or more processors **338** and memory **340** communicatively coupled with the one or more processors **338**. The memory **340** may store data defining an offline model **342** and a runtime model **344** as described elsewhere in the present disclosure. The computing device(s) **336** may also include a user interface **346** for enabling user input relating to assisted labelling functionality as described elsewhere in the present disclosure.

In some instances, aspects of some or all of the components discussed herein may include any models, algorithms, and/or machine learning algorithms. For example, some of the component(s) in the memory **318** may be implemented as a neural network. As can be understood in the context of this disclosure, a neural network may be trained using machine learning in which values of parameters of the network may be determined automatically from data during a training process, rather than being explicitly programmed by a human programmer.

EXAMPLE CLAUSES

A: A system comprising: a user interface; one or more processors; and one or more computer-readable media storing computer-executable instructions which, when executed by the one or more processors, cause the one or more processors to perform operations comprising: obtaining sensor data representative of an environment at a first time step; and pointwise data indicating, for the first time step and a plurality of further time steps, a pointwise measurement of a state of an object detected within the environment; determining a refined estimate of the state of the object at the first time step based on the pointwise measurement of the state of the object at the first time step and pointwise measurements of the state of the object at the plurality of further time steps; generating, using the refined estimate of the state of the object, a proposed annotation associated with the object at the first time step; rendering, via the user interface: a visual representation of the environment at the first time step, derived from the sensor data; and a visual representation of the proposed annotation; receiving, via the user interface, user input indicating a modified annotation associated with the object at the first time step; training a machine learning model using the sensor data and the modified annotation associated with the object at the first time step; and providing the trained machine learning model to an autonomous vehicle for use in controlling the autonomous vehicle.

B: A system as described in clause A, wherein the state of the first object comprises at least one of a position, velocity, yaw and yaw rate.

C: A system as described in clause A or B, wherein the plurality of time steps includes a time step later than the first time step.

D: A system as described in any of clauses A to C, The system of claim **1**, wherein: the proposed annotation associated with the first object instance is a first class label; the modified annotation associated with the first object instance is a second class label; and the second class label is different from the first class label.

E: A system as described in any of clauses A to D, wherein computer-executable instructions, when executed by the one or more processors, cause the one or more processors to perform operations comprising: generating a proposed annotation associated with the object at one of the plurality of further time steps in dependence on the modified annotation.

F: A computer-implemented method comprising: determining an estimate of a state of an object detected at a first time step, based on a pointwise estimate of the state of the object at the first time step and pointwise measurements of the state of the object at a plurality of further time steps; generating, using the estimate of the state of the object, a proposed annotation associated with the object at the first time step; rendering, via a user interface: a visual representation of the environment at the first time step; and a visual representation of the proposed annotation; receiving, via the user interface, user input indicating a user-approved annotation associated with the object at the first time step; and generating training data for a machine learning model for use in controlling an autonomous vehicle, based at least in part on the user-approved annotation.

G: A computer-implemented method as described in clause F, wherein the plurality of further time steps includes a time step later than the first time step.

H: A computer-implemented method as described in clause F or G, wherein determining the estimate of the state of the object comprises processing, by a smoother, the pointwise measurements of the state of the object at the first time step and the plurality of further time steps.

I: A computer-implemented method as described in any of clauses F to H, wherein determining the estimate of the state of the object comprises associating a the first instance of the object detected at the first time step with respective further instances of the object detected at the plurality of further time steps.

J: A computer-implemented method as described in any of clauses F to I, wherein associating the first instance of the object detected at the first time step with the respective further instances of the object detected at the plurality of further time steps comprises: determining a plurality of candidate track configurations comprising candidate groupings of instances of objects detected at the first time step and the plurality of further time steps; determining a most likely track configuration of the plurality of track configurations; and associating the first instance of the object with said respective further instances of the object in accordance with the determined most likely track configuration of the plurality of track configurations.

K: A computer-implemented method as described in any of clauses F to J, comprising: obtaining sensor data representative of the environment at the first time step; and deriving the visual representation of the environment from the sensor data.

L: A computer-implemented method as described in any of clauses F to K, wherein the state of the object comprises at least one of a position, velocity, yaw and yaw rate.

M: A computer-implemented method as described in any of clauses F to L, wherein: the proposed annotation comprises a first bounding box or bounding contour associated with the object; and the user-approved annotation comprises a second bounding box or bounding contour associated with the object.

N: A computer-implemented method as described in any of clauses F to M, wherein: the proposed annotation comprises a first class label; and the user-approved annotation comprises a second class label.

O: A computer-implemented method as described in any of clauses F to N, comprising generating a proposed annotation associated with the object at one of the plurality of further time steps in dependence on the user-approved annotation.

P: A computer-implemented method as described in any of clauses F to O, wherein the user-approved annotation is different from the proposed annotation.

Q: A computer-implemented method as described in any of clauses F to P, wherein the proposed annotation is a first proposed annotation, the method comprising: generating, using the estimate of the state associated with the object at the first time step, a second proposed annotation associated with the object at the first time step; and rendering, via the user interface, a visual representation of the second proposed annotation, wherein the user-approved annotation is a selection of the first proposed annotation or the second proposed annotation.

R: A computer-implemented method as described in any of clauses F to Q, comprising training the machine learning model using the generated training data.

S: A computer-implemented method as described in any of clauses F to R, comprising providing the trained machine learning model to an autonomous vehicle for use in controlling the autonomous vehicle.

T: One or more non-transitory computer-readable media storing instructions executable by one or more processors, wherein the instructions, when executed, cause the one or more processors to perform operations comprising: determining an estimate of a state of an object detected at a first time step, based on a pointwise estimate of the state of the object at the first time step and pointwise measurements of the state of the object at a plurality of further time steps; generating, using the estimate of the state of the object, a proposed annotation associated with the object at the first time step; rendering, via a user interface: a visual representation of the environment at the first time step; and a visual representation of the proposed annotation; receiving, via the user interface, user input indicating a user-approved annotation associated with the object at the first time step; and generating training data for a machine learning model for use in controlling an autonomous vehicle, based at least in part on the user-approved annotation.

While the example clauses described above are described with respect to one particular implementation, it should be understood that, in the context of this document, the content of the example clauses can also be implemented via a method, device, system, computer-readable medium, and/or another implementation. Additionally, any of examples A-T may be implemented alone or in combination with any other one or more of the examples A-T.

What is claimed is:

1. A system comprising:

a user interface;

one or more processors; and

one or more computer-readable media storing computer-executable instructions which, when executed by the one or more processors, cause the one or more processors to perform operations comprising:

obtaining:

sensor data representative of an environment at a first time step; and

pointwise data indicating, for the first time step and a plurality of further time steps, a pointwise measurement of a state of an object detected within the environment;

determining, by one or more first models, a refined estimate of the state of the object at the first time step based on the pointwise measurement of the state of the object at the first time step and pointwise measurements of the state of the object at the plurality of further time steps, at least one of the one or more first models configured to receive the pointwise data;

generating, by the one or more first models and using the refined estimate of the state of the object, a proposed annotation associated with the object at the first time step;

rendering, via the user interface:

a visual representation of the environment at the first time step, derived from the sensor data; and

a visual representation of the proposed annotation;

receiving, via the user interface, user input indicating a modified annotation associated with the object at the first time step;

training a machine learning model using the sensor data and the modified annotation associated with the object at the first time step, the machine learning model different to the one or more first models; and

providing the trained machine learning model to an autonomous vehicle for use in controlling the autonomous vehicle,

wherein at least one of the one or more first models comprises a first multi-hypothesis tracking model configured to generate multiple tracking hypotheses associated with estimated states of the object, the one or more models further comprising a first pruning algorithm configured to remove tracking hypotheses generated by the first multi-hypothesis tracking model; and

wherein the machine learning model comprises a second multi-hypothesis tracking model and a second pruning algorithm, the second pruning algorithm configured to remove tracking hypotheses generated by the second multi-hypothesis tracking model, the second pruning algorithm configured such fewer tracking hypotheses are maintained during object state estimation by the machine learning model than are maintained during object state estimation by the one or more first models.

2. The system of claim **1**, wherein the state of the object comprises at least one of a position, velocity, yaw and yaw rate.

3. The system of claim **1**, wherein the plurality of further time steps includes a time step later than the first time step.

4. The system of claim **1**, wherein:

the proposed annotation associated with the first object instance is a first class label;

the modified annotation associated with the first object instance is a second class label; and

the second class label is different from the first class label.

5. The system of claim **1**, wherein computer-executable instructions, when executed by the one or more processors, cause the one or more processors to perform operations comprising generating a proposed annotation associated with the object at one of the plurality of further time steps in dependence on the modified annotation.

6. A computer-implemented method comprising:

determining, by one or more first models, an estimate of a state of an object at a first time step, based on a pointwise measurement of the state of the object at the first time step and pointwise measurements of the state of the object at a plurality of further time steps, at least one of the one or more first models configured to receive the pointwise measurements;

generating, by the one or more first models and using the estimate of the state of the object, a proposed annotation associated with the object at the first time step;

rendering, via a user interface:

a visual representation of an environment containing the object at the first time step; and a visual representation of the proposed annotation;

receiving, via the user interface, user input indicating a user-approved annotation associated with the object at the first time step; and

generating training data for a machine learning model for use in controlling an autonomous vehicle, based at least in part on the user-approved annotation, the machine learning model different to the one or more first models,

wherein at least one of the one or more first models comprises a first multi-hypothesis tracking model configured to generate multiple tracking hypotheses associated with estimated states of the object, the one or more models further comprising a first pruning algorithm configured to remove tracking hypotheses generated by the first multi-hypothesis tracking model; and

wherein the machine learning model comprises a second multi-hypothesis tracking model and a second pruning algorithm, the second pruning algorithm configured to remove tracking hypotheses generated by the second multi-hypothesis tracking model, the second pruning algorithm configured such fewer tracking hypotheses are maintained during object state estimation by the machine learning model than are maintained during object state estimation by the one or more first models.

7. The computer-implemented method of claim **6**, wherein the plurality of further time steps includes a time step later than the first time step.

8. The computer-implemented method of claim **6**, wherein determining the estimate of the state of the object comprises processing, by a smoothing algorithm, the pointwise measurements of the state of the object at the first time step and the plurality of further time steps.

9. The computer-implemented method of claim **6**, wherein determining the estimate of the state of the object comprises associating a first instance of the object detected at the first time step with respective further instances of the object detected at the plurality of further time steps.

10. The computer-implemented method of claim **9**, wherein associating the first instance of the object detected at the first time step with the respective further instances of the object detected at the plurality of further time steps comprises:

determining a plurality of candidate track configurations comprising candidate groupings of instances of objects detected at the first time step and the plurality of further time steps;

determining a most likely track configuration of the plurality of track configurations; and

associating the first instance of the object with said respective further instances of the object in accordance with the determined most likely track configuration of the plurality of track configurations.

11. The computer-implemented method of claim **6**, comprising:

obtaining sensor data representative of the environment at the first time step; and

deriving the visual representation of the environment from the sensor data.

12. The computer-implemented method of claim **6**, wherein:

the proposed annotation comprises a first bounding box or bounding contour associated with the object; and

the user-approved annotation comprises a second bounding box or bounding contour associated with the object.

13. The computer-implemented method of claim **6**, wherein:

the proposed annotation comprises a first class label; and

the user-approved annotation comprises a second class label.

14. The computer-implemented method of claim **6**, comprising generating a proposed annotation associated with the object at one of the plurality of further time steps in dependence on the user-approved annotation.

15. The computer-implemented method of claim **6**, wherein the proposed annotation is a first proposed annotation, the method comprising:

generating, using the estimate of the state associated with the object at the first time step, a second proposed annotation associated with the object at the first time step; and

rendering, via the user interface, a visual representation of the second proposed annotation,

wherein the user-approved annotation is a selection of the first proposed annotation or the second proposed annotation.

16. The computer-implemented method of claim **15**, comprising providing the trained machine learning model to an autonomous vehicle for use in controlling the autonomous vehicle.

17. The computer-implemented method of claim **6**, comprising training the machine learning model using the generated training data.

18. The computer-implemented method of claim **6**, wherein the one or more first models are offline models, and wherein the machine learning model is a runtime model.

19. The computer-implemented method of claim **6**, comprising:

determining, by the one of more first models, the estimate of the state of the object at the first time step based at least in part on the pointwise measurement of the state of the object at the first time step and at least one pointwise measurement of the state of the object at a time step later than the first time step; and

wherein the machine learning model is configured to determine an estimate of a state of a further object at a second time step based at least in part on a pointwise measurement associated with the second time step and/or an time step earlier than the second time step, and excluding pointwise measurements associated with time steps later than the second time step.

20. One or more non-transitory computer-readable media storing computer-executable instructions which, when executed by one or more processors, cause the one or more processors to perform operations comprising:

determining, by one or more first models, a refined estimate of a state of an object at a first time step, based on a pointwise measurement of the state of the object at the first time step and pointwise measurements of the state of the object at a plurality of further time steps, at least one of the one or more first models configured to receive the pointwise measurements;

generating, by the one or more first models and using the refined estimate of the state, a proposed annotation associated with the object at the first time step;

rendering, via a user interface:

a visual representation of an environment containing the object at the first time step; and

a visual representation of the proposed annotation;

receiving, via the user interface, user input indicating a user-approved annotation associated with the object at the first time step; and generating training data for a machine learning model for use in controlling an autonomous vehicle, based at least part on the user-approved annotation, the machine learning model different to the one or more first models,

wherein at least one of the one or more first models comprises a first multi-hypothesis tracking model configured to generate multiple tracking hypotheses associated with estimated states of the object, the one or more models further comprising a first pruning algorithm configured to remove tracking hypotheses generated by the first multi-hypothesis tracking model; and

wherein the machine learning model comprises a second multi-hypothesis tracking model and a second pruning algorithm, the second pruning algorithm configured to remove tracking hypotheses generated by the second multi-hypothesis tracking model, the second pruning algorithm configured such fewer tracking hypotheses are maintained during object state estimation by the machine learning model than are maintained during object state estimation by the one or more first models.

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