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(54) **ACTIVE LEARNING BASED ON CONFUSION MATRIX CALIBRATED UNCERTAINTY FOR OBJECT CLASSIFICATION IN VISUAL PERCEPTION TASKS IN A VEHICLE**

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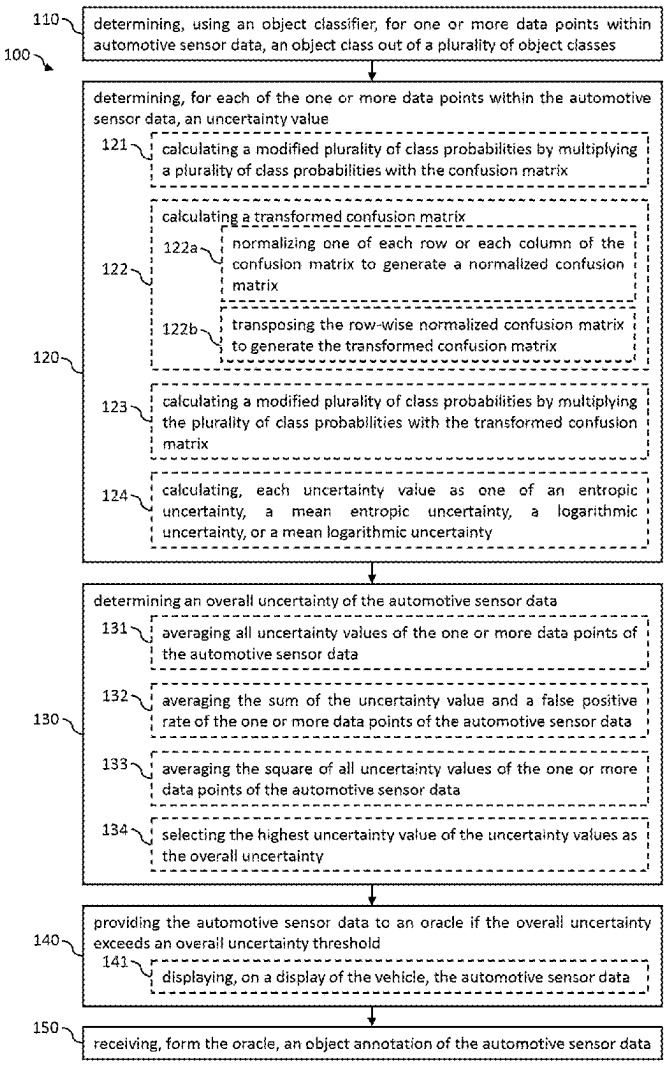
(57) **ABSTRACT**

The present disclosure relates to enabling active learning for object classification in visual perception tasks in a vehicle. To this end, an object class out of a plurality of object classes is determined for one or more data points within automotive sensor data. Further, an uncertainty value for each of the one or more data points within the automotive sensor data based on a plurality of class probabilities and a confusion matrix is determined. Based on the determined uncertainty values, an overall uncertainty of the automotive sensor data is determined. Then, the automotive sensor data are provided to an oracle if the overall uncertainty exceeds an overall uncertainty threshold. Finally, an object annotation of the automotive sensor data is received from the oracle.



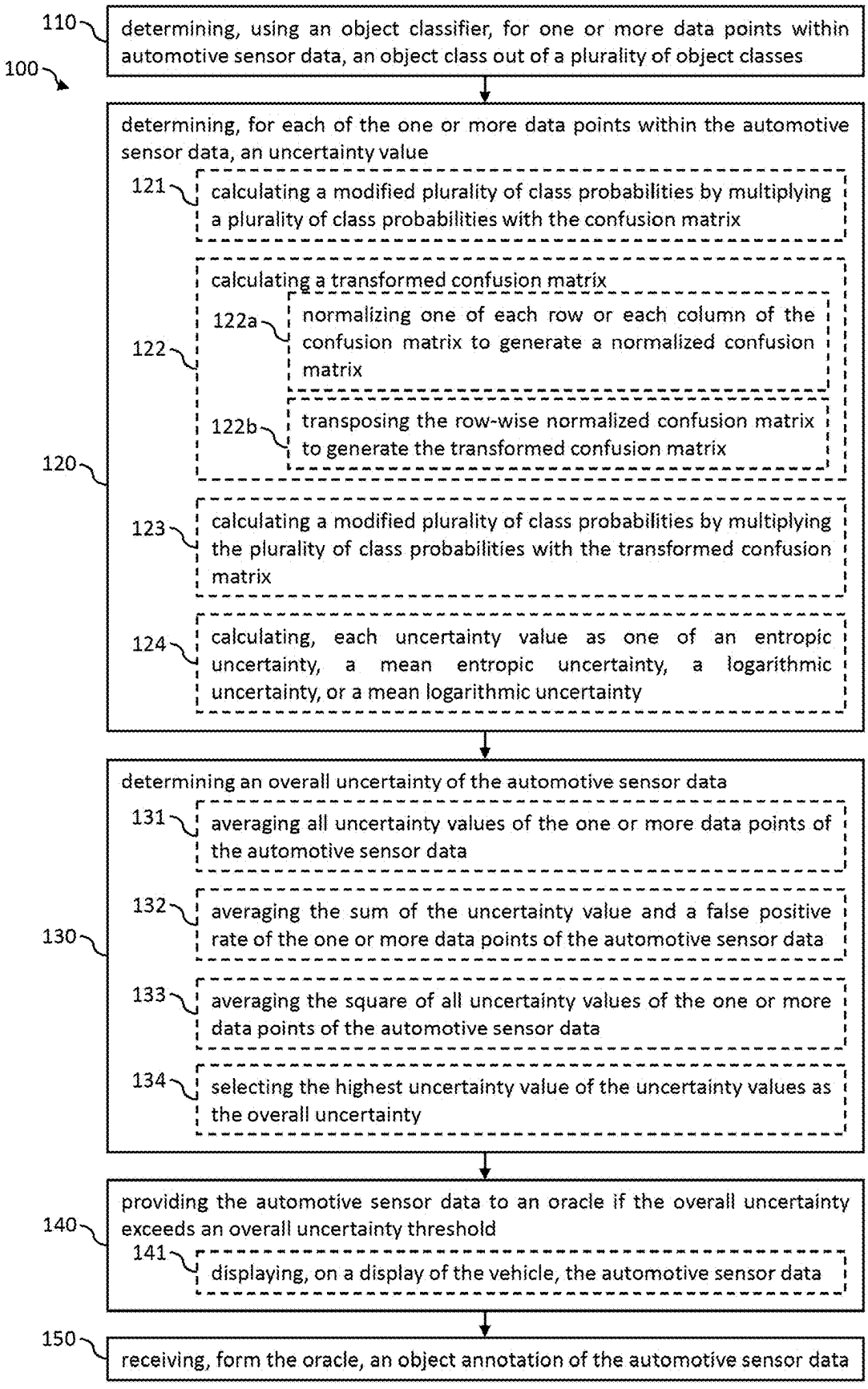

100
110
determining, using an object classifier, for one or more data points within automotive sensor data, an object class out of a plurality of object classes
120
determining, for each of the one or more data points within the automotive sensor data, an uncertainty value
121
calculating a modified plurality of class probabilities by multiplying a plurality of class probabilities with the confusion matrix
122
calculating a transformed confusion matrix
122a
normalizing one of each row or each column of the confusion matrix to generate a normalized confusion matrix
122b
transposing the row-wise normalized confusion matrix to generate the transformed confusion matrix
123
calculating a modified plurality of class probabilities by multiplying the plurality of class probabilities with the transformed confusion matrix
124
calculating, each uncertainty value as one of an entropic uncertainty, a mean entropic uncertainty, a logarithmic uncertainty, or a mean logarithmic uncertainty
130
determining an overall uncertainty of the automotive sensor data
131
averaging all uncertainty values of the one or more data points of the automotive sensor data
132
averaging the sum of the uncertainty value and a false positive rate of the one or more data points of the automotive sensor data
133
averaging the square of all uncertainty values of the one or more data points of the automotive sensor data
134
selecting the highest uncertainty value of the uncertainty values as the overall uncertainty
140
providing the automotive sensor data to an oracle if the overall uncertainty exceeds an overall uncertainty threshold
141
displaying, on a display of the vehicle, the automotive sensor data
150
receiving, form the oracle, an object annotation of the automotive sensor data

Fig. 1

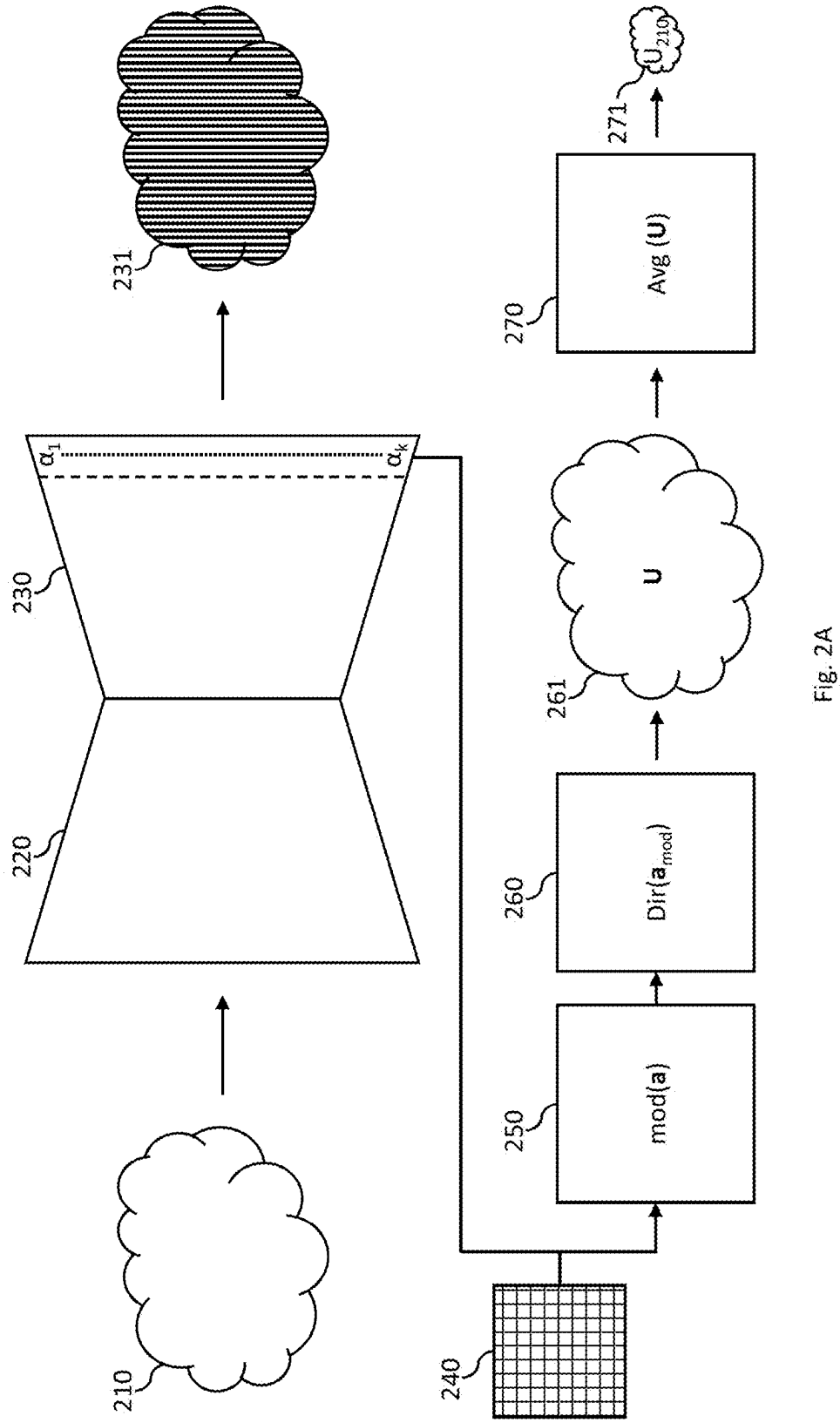

231
α_1
α_k
230
220
210
240
250
mod(a)
260
Dir(a_{mod})
261
U
270
Avg (U)
271
U_{210}

Fig. 2A

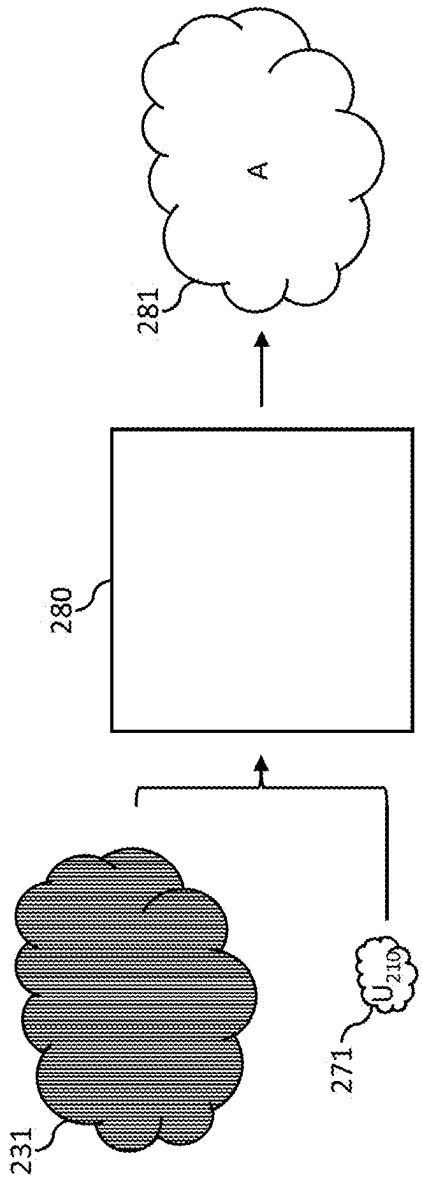


Fig. 2B

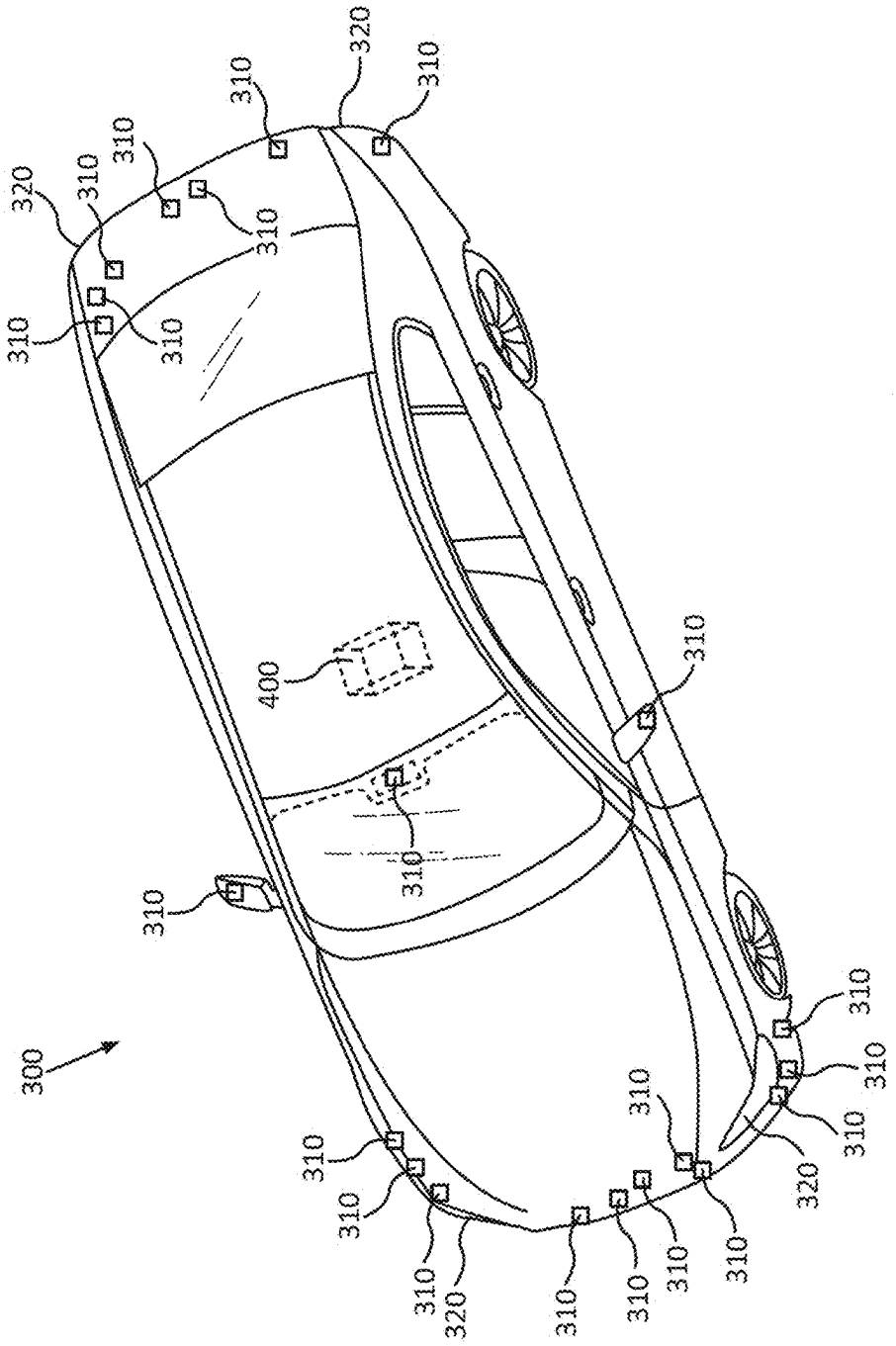


Fig.3

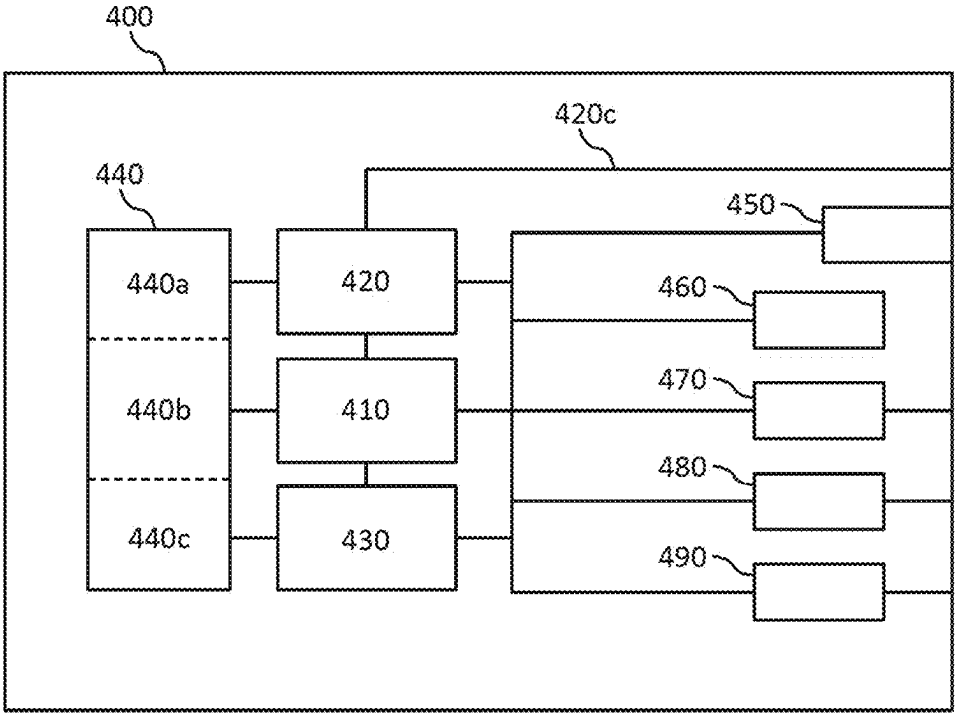


Fig.4

ACTIVE LEARNING BASED ON CONFUSION MATRIX CALIBRATED UNCERTAINTY FOR OBJECT CLASSIFICATION IN VISUAL PERCEPTION TASKS IN A VEHICLE

CROSS REFERENCE TO RELATED APPLICATION

[0001] This application claims priority under 35 U.S.C. § 119 from European Patent Application No. 24158249.3, filed Feb. 16, 2024, the entire disclosure of which is herein expressly incorporated by reference.

TECHNICAL FIELD

[0002] The invention generally relates to active learning and more precisely to active learning in the context of perception tasks in vehicles configured to provide at least partial driving automation.

BACKGROUND

[0003] To enable at least partial driving automation, a vehicle needs to accurately perform automotive perception tasks, such as object classification, object detection or semantic segmentation. These perception tasks are usually performed by machine learning algorithms, which need to be trained on large datasets and may be further improved even once the vehicle is deployed in traffic. One way of ensuring accurate performance of automotive perception tasks by the machine learning algorithms is to train the machine learning algorithms with large, labeled datasets which indicate the outcome of the respective automotive perception task. However, since such labeling may be performed manually, large, labeled datasets to train machine learning algorithms for at least partial driving automation may be costly to generate. To overcome this issue, active learning may be used, i.e., a given machine learning algorithm may be inferenced on unlabeled data and may request that a subset of the unlabeled data be labeled based on active learning criteria. However, the active learning criteria generally need to be determined in a way which improves a given machine learning algorithm and in the context of at least partial driving automation need to enable achieving the level of accuracy of a machine learning algorithm required for of at least partial driving automation.

[0004] It is therefore an objective of the present disclosure to provide active learning criteria which enable the training and improvement of a machine learning algorithm configured to perform an automotive perception task in a manner ensuring the accuracy required for at least partial driving automation.

SUMMARY OF THE INVENTION

[0005] To achieve this objective, the present disclosure provides a method configured to enable active learning for object classification in visual perception tasks in a vehicle configured to provide at least partial driving automation based on the object classification. The method comprises determining, using an object classifier, for one or more data points within automotive sensor data, an object class out of a plurality of object classes. Each object class corresponds to an object type encounterable in a driving environment of the vehicle. The method further comprises determining, for each of the one or more data points within the automotive sensor data, an uncertainty value based on a plurality of class probabilities and a confusion matrix. Each uncertainty value is indicative of an uncertainty of the object class determination. Each class probability is indicative, for each of the one or more data points, of the probability of each data point being indicative of a corresponding object class. The confusion matrix is indicative, for each object class of the plurality of object classes, of a probability of the object classifier determining, for a given object class, each of the object classes of the plurality of object classes. The method further comprises determining an overall uncertainty of the automotive sensor data based on the uncertainty values of the one or more data points. The method further comprises providing the automotive sensor data to an oracle if the overall uncertainty exceeds an overall uncertainty threshold. Finally, the method comprises receiving, from the oracle, an object annotation of the automotive sensor data.

[0006] The present disclosure further provides an automotive control unit. The automotive control unit comprises at least one processing unit and a memory coupled to the at least one processing unit and configured to store machine-readable instructions. The machine-readable instructions cause the at least one processing unit to determine, using an object classifier, for one or more data points within automotive sensor data, an object class out of a plurality of object classes. Each object class corresponds to an object type encounterable in a driving environment of the vehicle. The machine-readable instructions further cause the at least one processing unit to determine, for the one or more data points within the automotive sensor data, an uncertainty value based on a plurality of class probabilities and a confusion matrix. Each uncertainty value is indicative of an uncertainty of the object class determination. Each class probability is indicative, for each of the one or more data points, of the probability of each data point belonging to a corresponding object class. The confusion matrix is indicative, for each object class of the plurality of object classes, of a probability of the object classifier determining, for a given object class, each of the object classes of the plurality of object classes. The machine-readable instructions further cause the at least one processing unit to determine an overall uncertainty of the automotive sensor data based on the uncertainty values of the one or more data points. The machine-readable instructions further cause the at least one processing unit to provide the automotive sensor data to an oracle if the overall uncertainty exceeds an overall uncertainty threshold. Finally, the machine-readable instructions further cause the at least one processing unit to receive, from the oracle, an object annotation of the automotive sensor data.

[0007] The present disclosure further provides a vehicle comprising the automotive control unit.

BRIEF DESCRIPTION OF THE DRAWINGS

[0008] Examples of the present disclosure will be described with reference to the following appended drawings, in which like reference signs refer to like elements.

[0009] FIG. **1** shows a flowchart of a method configured to enable active learning for object classification in visual perception tasks in a vehicle configured to provide at least partial driving automation based on the object classification according to examples of the present disclosure.

[0010] FIGS. **2**A and **2**B illustrate the processing of automotive sensor data in accordance with the method of FIG. **1** according to examples of the present disclosure.

[0011] FIG. **3** illustrates a vehicle according to examples of the present disclosure.

[0012] FIG. **4** illustrates an automotive control unit according to examples of the present disclosure.

[0013] It should be understood that the above-identified drawings are in no way meant to limit the present disclosure. Rather, these drawings are provided to assist in understanding the present disclosure. The person skilled in the art will readily understand that aspects of the present invention shown in one drawing may be combined with aspects in another drawing or may be omitted without departing from the scope of the present disclosure.

DETAILED DESCRIPTION

[0014] The present disclosure generally provides a method configured to enable active learning for object classification in visual perception tasks in a vehicle configured to provide at least partial driving automation based on the object classification. In addition, the present disclosure generally provides an automotive control unit configured to execute instructions implementing said method and a vehicle including said automotive control unit.

[0015] Typically, a vehicle is equipped with various automotive sensors providing automotive sensor data indicative of a driving environment of the vehicle. To infer objects from the automotive sensors, the vehicle is configured to identify objects within the automotive sensor data. The identified objects are then used by advanced driver assistance systems (ADAS) to control longitudinal and lateral motion of the vehicle. To safely identify and to thereby safely enable longitudinal and lateral control of the vehicle, the vehicle employs object detection and classification within the automotive sensor data which has been trained on labeled data. However, given the effectively innumerable number of visual appearances of objects in the driving environment of the vehicle, labeled training data cannot cover all potential visual appearances of a given object, such as a pedestrian or other vulnerable road user (VRU).

[0016] To account for the fact that training data may never cover all possible visual appearances of objects encounterable in the driving environment of the vehicle, the present disclosure proposes an active learning approach for object classification in vehicles, which decides based on uncertainty values, which have been calibrated using a confusion matrix, whether to request an oracle to annotate the automotive sensor data. Based on this annotation, the accuracy of the object detection and classification performed by the vehicle and thus the safety of the longitudinal and lateral control of the vehicle by one or more ADASs may be improved.

[0017] Uncertainty in the context of the present disclosure refers to the uncertainty of the object classification performed by the vehicle regarding the classification of objects within the automotive sensor data. In other words, the uncertainty of an object classifier indicates how probable it is that the classification of an object within the automotive sensor data as being indicative of a specific object type may be wrong. To this end, the vehicle is configured to determine an uncertainty of an object classification of one or more data points within the automotive sensor data, e.g., based on a Dirichlet distribution. In addition, the uncertainty determination proposed by the present disclosure is rendered more accurate by calibrating, i.e., determining, the uncertainty values based on a confusion matrix. A confusion matrix indicates, for a given object classifier, the probability of the object classifier classifying an object, which belongs to a given object class, as belonging to any one of the object classes, which the object classifier is capable of identifying. For example, if an object classifier is capable of identifying five object classes, the confusion matrix includes five columns and five rows, with each column identifying how often an expected object class has been identified. That is, each column indicates the probability that the expected object class has been identified and the probability that each of the other four classes has been identified.

[0018] The accordingly determined uncertainty values are then used to determine an overall uncertainty of the automotive sensor data, which may be determined based on various averaging approaches or by selecting the highest uncertainty value out of the determined uncertainty values.

[0019] If the overall uncertainty exceeds an overall uncertainty threshold, the automotive sensor data are provided to the oracle for annotation, i.e., identification, by the oracle, of the object classes of the one or more data points within the automotive sensor data. The accordingly annotated patches are received by the vehicle and used by the vehicle to improve the object detection and classification and to thereby improve the safety of the longitudinal and lateral control by the one or more ADAS of the vehicle.

[0020] This general concept will be explained with reference to the appended drawings, with FIG. **1** providing a flowchart of a method **100** configured to enable active learning for object classification in visual perception tasks in a vehicle configured to provide at least partial driving automation and FIG. **2** illustrating the processing of automotive sensor data in accordance with the method of FIG. **1**. In addition, FIG. **3** illustrates a vehicle according to the present disclosure and FIG. **4** illustrates an automotive controller configured to perform method **100**.

[0021] It will be understood that dashed boxes in FIG. **1** illustrate optional steps of method **100**.

[0022] Method **100** is configured to enable active learning for object classification in visual perception tasks in a vehicle, such as vehicle **300** of FIG. **3**, configured to provide at least partial driving automation.

[0023] Vehicle **200** in the context of the present disclosure refers to any kind of motor vehicle configured to transport people and/or cargo. The motor of vehicle **300** may be any kind of motor, such as an electric motor or an internal combustion engine. Vehicle **300** may be a passenger vehicle. It will however be understood that the vehicle **300** may also be a bus, a truck or any other kind of vehicle including one or more sensors **310** and an automotive control unit **400** enabling vehicle **200** to provide at least partial driving automation. That is, automotive control unit **400** and one or more sensors **310** are configured to enable at least partial driving automation, i.e., level 2 as defined in standard J3016 of SAE International. Accordingly, method **100** enables improving the accurate performance of object classification in visual perception tasks within automotive control unit **400** to increase safe control of the longitudinal motion and the lateral motion of vehicle **300**. It will be understood that method **100**, automotive control unit **400** and one or more

sensors **310** may enable higher levels of automation, e.g., up to and including level 5 as defined in standard J3016 of SAE International.

[0024] The one or more sensors **310** may be configured to capture automotive sensor data indicative of a driving environment of vehicle **300**, which may provide the environmental awareness enabling at least partial driving automation. For example, the one or more sensors **310** may provide vehicle **300** with information on the position and size of other vehicles or with information regarding road surface markings, which are extracted from the automotive sensor data based on the object classification performed by the machine learning algorithm. To this end, the one or more sensors **310** may be radar sensors, which may be configured to emit radio waves to determine a distance, an angle and a velocity of objects around the vehicle based on the reflected radio waves. The one or more sensors **310** may be light detection and ranging (LIDAR) sensors, which are configured to emit laser beams to determine a distance, an angle and a velocity of objects around vehicle **300** based on the reflected laser beams. The one or more sensors **310** may be cameras, which capture images of the environment of the vehicle. The one or more sensors **310** may be thermographic cameras, which capture images of the environment of vehicle **300** based on infrared radiation. It will be understood that LIDAR sensors, radar sensors or cameras are merely provided as examples of sensor types of the one or more sensors **310**. For example, the one or more sensors **310** may also be ultrasonic sensors. More generally, the one or more sensors **310** may be any type of sensor capable of capturing sensor data indicative of the environment of vehicle **300**. It will further be understood that the one or more sensors **310** may include multiple sensors of various types of sensors. Further, the one or more sensors **310** of the same type may exhibit different properties, e.g., by being configured to capture sensor data at different ranges, such as a close range, a middle range and a far range. For example, vehicle **300** may include three close range radar sensors each at a front and a back of vehicle **300**, a middle range to far range radar sensor at the back of vehicle **300**, a LIDAR sensor at the front of vehicle **300**, a rear-facing camera at the back of vehicle **300**, a front-facing camera at the front of the vehicle, a front-facing camera at the rear-view mirror and a rear-facing close range to middle range radar sensor in each door-mounted outer rear view mirror. It will be understood that vehicle **300** may include more or fewer automotive sensors than shown in FIG. **3** and discussed in the above example.

[0025] It will be understood that automotive sensor data in the sense of the present application may be any kind of data, such as an image frame, a data cloud or any other type of data structure suitable to include data from automotive sensors **310** and to thereby convey information indicative of the driving environment of vehicle **300**. To illustrate this fact, automotive sensor data is illustrated as automotive sensor data **210** in the form of a cloud in FIGS. **2**A and **2**B. Single data elements within automotive sensor data **210** will be referred to throughout this disclosure as data points and may be pixels in the example of automotive sensor data **210** being a frame.

[0026] Automotive control unit **400** will be discussed in more detail below with reference to FIG. **4**.

[0027] In the context of the present disclosure, visual perception task refers to any kind of task identifying one or more object classes within automotive sensor data **210** captured by the one or more sensors **310**. The visual perception task may identify within automotive sensor data provided by a camera included in vehicle **300** whether vehicle **300** is located on a controlled-access highway, a limited-access road, an arterial road, a local road or a parking lot. In this case, the one or more object classes correspond to the type of road on which vehicle **300** may be located. Further, the visual perception task may identify within automotive sensor data provided by a LIDAR sensor and multiple cameras included in vehicle **200** other vehicles and the type of vehicle, road surface markings and the type of road surface marking, road signs and the type of road sign, vulnerable road users (VRUs) as well as traffic lights and the indication state of the traffic light. Accordingly, the object classes of the plurality of object classes may correspond to any possible road user, road traffic control device and road surface marking as well as any other type of element encounterable in the driving environment of the vehicle **200** relevant for enabling at least partial driving automation. More generally, the visual perception task may thus be any perception task determining the class of objects in the vicinity of vehicle **200**, with the objects referring to both a determination of the general environment of vehicle **200** as well as a determination of individual elements in the vicinity of vehicle **200**. In this context, it will accordingly be understood that object classification in the context of the present disclosure may identify the classes of multiple objects within automotive sensor data **210** and is not limited to the identification of a single object class within automotive sensor data **210**.

[0028] In the context of the visual perception task, active learning is thus to be understood in the context of the present disclosure to refer to an object classifier, which performs at least a part of the visual perception task requesting an oracle to label the automotive sensor data, i.e., to determine one or more object classes within the automotive sensor data.

[0029] The object classifier may be any kind of machine learning algorithm which has been trained based on training automotive sensor data to classify objects in the driving environment of the vehicle, which has been trained to perform a visual perception task as defined above. Training automotive sensor data may be unlabeled, partially labeled or fully labeled. In other words, the training automotive sensor data may include the corresponding object classes in addition to the automotive sensor data. However, given the active learning functionality discussed above and described in detail below, the training automotive sensor data need not be fully labeled. The machine learning algorithm may be a feature extractor configured to extract objects from the automotive sensor data and to determine the object class of the extracted objects. To this end, the machine learning algorithm may be an artificial neural network (ANN), an autoencoder or a data clustering algorithm. For example, if the object classifier is implemented as a neural network configured to perform at least the determination of object classes, a plurality of activation levels of an output layer of the neural network may correspond to a plurality of class probabilities.

[0030] It will be understood that a class probability in the context of the present disclosure indicates for a given data point of the automotive sensor data the probability of the given data point being indicative of a corresponding object class. Taking an object classifier configured to identify 100

different object classes as an example, the plurality of class probabilities in this example includes 100 class probabilities with each class probability indicating, for a given data point, the probability of the given data point being indicative of each of the 100 classes. It will be understood that the object classifier may be able to identify any number of classes, such as 10,000 or 10, depending on the type of object classification the object classifier is designed to perform within the context of the visual perception task and the at least partial driving control of vehicle **300**. Based on the highest probability out of the plurality of class probabilities, the object classifier may determine the given data point as being indicative of the object class corresponding to the highest class probability.

[0031] As illustrated in FIG. **2**A, the object classifier may be implemented as an autoencoder including an object classification encoder **220** and an object classification decoder **230**, which together are configured to detect, for one or more data points within the automotive sensor data **210**, one or more object classes **231**. In FIG. **2**A object classes **231** are illustrated as a data cloud similar in shape to automotive sensor data **210** to illustrate that the object classes determined within automotive sensor data can be considered attached to their corresponding data points within automotive sensor data.

[0032] More precisely, object classification encoder **220** may be configured to generate a latent space. The latent space may include all activation values of all neurons of the output layer of shared encoder **220**, which corresponds to the bottleneck of the autoencoder. Object class decoder **230** may be configured to determine for one or more data points within automotive sensor data **210** a corresponding object class **231** based on the latent space. Object class decoder **230** may determine the corresponding object class **231** for one or more data points within automotive sensor data **210** based on the highest class probability within the plurality of class probabilities as discussed above.

[0033] In step **110**, method **100** determines for one or more data points within automotive sensor data **210** an object class **231** out of the plurality of object classes. In other words, method **100** determines for one or more data points within automotive sensor data **210** a corresponding object class **231**. The processing performed by step **110** is performed by the object classifier discussed above and is illustrated in FIG. **2**A by object class encoder **220** and object class decoder **230** one or more object classes **231** within automotive sensor data **210**.

[0034] In step **120**, method **100** determines for each of the one or more data points within automotive sensor data **210** an uncertainty value **261**. Each uncertainty value **261** is indicative of an uncertainty of the object class determination, i.e., the object classification performed by the object classifier. Accordingly, method **100** determines an uncertainty value **261** for each object class **231** determined in step **110**.

[0035] Each uncertainty value is based on the plurality of class probabilities discussed above. Since the plurality of class probabilities indicates how likely it is that a given data point within automotive sensor data **210** is indicative of each of the object classes determinable by the object classifier, the class probabilities corresponding to the object classes not identified as being indicated by the given data point may be used as a measure of the uncertainty of the object classification. Based on this fact, various probability analysis approaches may be used. However, In the context of the present disclosure, the plurality of class probabilities is considered in conjunction with the confusion matrix, i.e., the determination of the uncertainty values in step **120** is based on both the plurality of class probabilities and the confusion matrix. Accordingly, before performing any of the various probability analysis approaches to determine the one or more uncertainty values **261**, the plurality of class probabilities and the confusion matrix are processed, as part of step **120**.

[0036] As briefly discussed above, confusion matrix **240** is indicative, for each object class of the plurality of object classes, of a probability of the object classifier determining, for a given object class, each of the object classes of the plurality of object classes. Taking an object classifier capable of identifying three different object classes within automotive sensor data **210** as an example, the confusion matrix may be expressed as shown in equation (1):

$$M = \begin{pmatrix} p_{11} & p_{12} & p_{13} \\ p_{21} & p_{22} & p_{23} \\ p_{31} & p_{31} & p_{33} \end{pmatrix} \quad (1)$$

In equation (1), M denotes the confusion matrix and p_{11} to p_{33} denote the probability that for a given automotive sensor data input indicative of a given object class **231** one of the three object classes **231** is identified. Each column corresponds to a given automotive sensor data input indicative of a given object class **231**. That is, the first column indicates that the input received by the object classifier is indicative of the first object class **231**, the second column indicates that the input received by the object classifier is indicative of the second object class **231** and the third column indicates that the input received by the object classifier is indicative of the third object class **231**. Each row indicates the actually determined object class for a given input. Taking probability p_{31} as an example, probability p_{31} indicates that the object classifier has determined the third object class **231** for an input indicative of the first object class **231**. Accordingly, the first number of each index of the probabilities included in confusion matrix indicates the index of the determined object class and the second number of each index of the probabilities included in confusion matrix indicates the index of the actual object class. It follows from this fact that the probabilities on the diagonal of confusion matrix **240** denote the probabilities that the object classifier correctly determines an object class for a given input. The probabilities outside of the diagonal of the confusion matrix thus indicate the probabilities of a wrong determination of a given object class. The confusion matrix thus indicates the general probabilities of the object classifier, i.e., object classification decoder **230**, of making correct and wrong determinations of the object classes **231** within automotive sensor data **210**. By contrast the class probabilities indicate for each data point the probability that a given data point within automotive sensor data **210** is indicative of a given object class **231**.

[0037] The confusion matrix may be determined with labeled training data after the training of the object classifier. That is, the confusion matrix may be determined after the training of the object classifier to determine how often the object classifier correctly and incorrectly determines object classes **231** within automotive sensor data **210**.

[0038] It will be understood that the confusion matrix may include probabilities, as discussed above, or absolute values indicative of the probabilities. That is, assuming as an example that the object classifier is provided with 50 labeled automotive sensor data sets for each of the three example classes discussed above, each entry may indicate how many of these 50 labeled sets were determined as being indicative of a given object class **231** with each column summing up to 50.

[0039] Method **100** uses the plurality of class probabilities and confusion matrix **240** in step **120** to determine uncertainty values **261** for one or more of the data points within automotive sensor data **210**. To this end, step **120** may include step **121** or steps **122** and **123** to determine a basis on which uncertainty values **261** may be determined.

[0040] In step **121**, method **100** may calculate a modified plurality of class probabilities by multiplying the plurality of class probabilities with confusion matrix **240**. That is, the modified plurality of class probabilities as calculated in step **121** may be indicative of the combined probability of a given data point being indicative of each of the object classes **231** and the probability of the object classifier determining any of the object classes **231** when provided with automotive sensor data **210** indicative of one of the object classes **231**. The calculation performed in step **121** may be expressed as shown in equation (2).

$$\tilde{\alpha} = \alpha * M \tag{2}$$

In equation (2), $\tilde{\alpha}$ denotes the modified plurality of class probabilities, α denotes the plurality of class probabilities and M denotes the confusion matrix **240**.

[0041] Alternatively, method **100** may calculate in step **122** a transposed confusion matrix. To this end, step **122** may comprise steps **122***a* and **122***b*. In step **122***a*, method **100** may normalize one of each row or each column of confusion matrix **240** to generate a normalized confusion matrix. That is, the probabilities in the normalized confusion matrix may be normalized either with regard to the provided input, i.e., column-wise, or with regard to the determined object class **231**, i.e., row-wise. Both approaches lead to a more accurate uncertainty determination. In step **122***b*, method **100** may transpose the normalized confusion matrix to generate the transposed confusion matrix. The transposed confusion matrix may lead to a more balanced weighting of the normalized probabilities. Following the calculation of the transposed confusion matrix, method **100** may, in step **123** calculate the modified plurality of class probabilities $\tilde{\alpha}$ by multiplying the plurality of class probabilities with the transposed confusion matrix M^T, as shown in equation (3).

$$\tilde{\alpha} = \alpha * M^T \tag{3}$$

[0042] As discussed above, various probability analysis approaches may be used to determine uncertainty values **261** in step **120** of method **100**. For example, the plurality of class probabilities as well as the modified plurality of class probabilities may be considered to correspond to concentration parameters of a Dirichlet distribution Dir(α). Accordingly, based on the modified plurality of class probabilities of the one or more data points within automotive sensor data **210**, each uncertainty value **261** may be calculated based on the corresponding Dirichlet distribution, as shown in equation (4):

$$U_{mean} = \frac{C}{\sum_{k=1}^{C} \tilde{a}_k} \tag{4}$$

In equation (4), U_{mean} denotes uncertainty value **261** as an average uncertainty, C denotes the number of classes the object classifier is configured to identify and $\tilde{\alpha}_k$ denotes a concentration parameter of the Dirichlet Distribution, i.e., the modified class probabilities.

[0043] In addition to the uncertainty calculation of equation (4), method **100** may as part of step **120** also determine the uncertainty values **261** in other ways. To this end, step **120** may further include a step **124**, in which method **100** may calculate, based on the modified plurality of class probabilities, each uncertainty value (**261**) as one of an entropic uncertainty, a mean entropic uncertainty, a logarithmic uncertainty, or a mean logarithmic uncertainty.

[0044] Entropic uncertainty may be calculated as shown in equation (5):

$$U_{ent} = H(a) = \sum_{k=1}^{C} \frac{\tilde{a}_k}{\tilde{a}_0} * \log \frac{\tilde{a}_k}{\tilde{a}_0} \tag{5}$$

In equation (5), in addition to the previously introduced parameters, U_{ent} and H(a) denote the entropic uncertainty.

[0045] Mean entropic uncertainty may be calculated as shown in equation (6):

$$U_{mean_ent} = U_{mean} \times U_{ent} \tag{6}$$

Accordingly, mean entropic uncertainty corresponds to the multiplication of entropic uncertainty and average uncertainty.

[0046] Logarithmic uncertainty may be calculated as shown in equation (7):

$$U_{log_ent} = \log(H_{max}(K)) - \log(H_{max}(K) - U_{ent}) \tag{7}$$

In other words, Logarithmic uncertainty may be calculated based on the maximum entropic uncertainty calculated based on the sum in equation (5).

[0047] Finally, mean logarithmic uncertainty may be calculated as shown in equation (8):

$$U_{mean_log_ent} = U_{mean} \times U_{log_ent} \tag{8}$$

[0048] In FIG. **2**A, the exemplary determination of the uncertainty values **261** is illustrated by class probability modification **250** and Dirichlet distribution determination **260**. Class probability modification **250** is labelled mod(a) and receives the activation values of the last layer of object

detection decoder **230**, i.e., the plurality of class probabilities of each of the one or more data points within automotive sensor data **210**. That is, the plurality of class probabilities of each of the one or more data points within automotive sensor data **210** may, in some examples of the present disclosure, correspond to the activation values of the output layer of object detection decoder **230**. Class probability modification **250** may perform any of steps **121** to **123**, i.e., may be configured to generate the modified plurality of class probabilities. Dirichlet distribution determination **260** receives the modified plurality of class probabilities from class probability modification **250** and is configured to calculate the uncertainty values **261** as discussed above, e.g., by implementing step **124**.

[0049] In step **130**, method **100** determines an overall uncertainty U_{210} of automotive sensor data **210** based on the uncertainty values **261** of the one or more data points determined in step **120**. Overall uncertainty U_{210} is indicative of the overall uncertainty of the determination of object classes **231** within automotive sensor data. To determine overall uncertainty U_{210} to reflect this overall uncertainty, method **100** may determine in one of the options of steps **131** to **134**.

[0050] In step **131**, method **100** may average all uncertainty values **261** of the one or more data points of the automotive sensor data **210**, as shown in equation (9):

$$U_{210} = \frac{1}{D} * \sum_{i=1}^{D} U_{261,i} \tag{9}$$

In equation (9), D denotes the number of data points.

[0051] In step **132**, method **100** may average the sum of the uncertainty values **261** and a false positive rate of the one or more data points of the automotive sensor data **210**. The false positive rate may correspond to a probability of a given object class **231** being wrongly determined for a given data point divided by the sum of the probability of the given object class **231** being wrongly determined for a given data point and a probability of the given object class **231** being correctly not determined. The false positive rate FPR may be expressed as in equation (10):

$$FPR = \frac{p_{falsely_detected}}{p_{falsely_detected} + p_{correctly_not_detected}} \tag{10}$$

In equation (**10**) $p_{falsey_detected}$ denotes the probability that a given object class **231** is detected even though a given data point within automotive sensor data **210** is not indicative of the given object class **231** and $p_{correctly_not_detected}$ denotes the probability that a given object class **231** is not detected and indeed no data point within automotive sensor data **210** is indicative of the given object class **231**. Based on the false positive rate FPR, the overall uncertainty may be calculated in step **132** as shown in equation (11):

$$U_{210} = \frac{1}{D} * \sum_{i=1}^{D} U_{261,i} * FPR_i \tag{11}$$

[0052] In step **132**, method **100** may average the square of all uncertainty values **261** of the one or more data points of the automotive sensor data **210**, as shown in equation (12).

$$U_{210} = \frac{1}{D} * \sum_{i=1}^{D} (U_{261,i})^2 \tag{12}$$

[0053] Finally, in step **134** method **100** may selecting the highest uncertainty value **261** determined in step **120** as the overall uncertainty.

[0054] In step **140**, method **100** provides the automotive sensor data **210** to oracle **280** if overall uncertainty U_{210} exceeds an overall uncertainty threshold. The overall uncertainty threshold may correspond to a sum of an average overall uncertainty and at least one standard deviation of the average overall uncertainty. That is, method **100** may provide the automotive sensor data to oracle **280** if overall uncertainty U_{210} of automotive sensor data **210** deviates by at least one standard deviation from an average overall uncertainty of the object determination performed by object detection decoder **230**. Accordingly, automotive sensor data **210** are provided to oracle **280** only if automotive sensor data **210** are considered outliers in terms of a standard deviation.

[0055] Oracle **280** may be a cloud-based object classification service, such as a larger object classifier provided on a backend of a manufacturer of vehicle **300** or a large crowd-sourced database providing data-to-text conversion based on a large database of annotated data.

[0056] Oracle **280** may be a user of vehicle **300**, in which case step **140** may include step **141**. In step **141**, method **100** may display to the driver on a display of vehicle **300** automotive sensor data **210**.

[0057] Finally, in step **150**, method **100** receives from the oracle **280** an object annotation **281** of the automotive sensor data That is, method **100** in step **150** receives automotive sensor data **210** with an indication which object class or potentially object classes are included in automotive sensor data **210**. Method **100** then uses the one or more object annotations **281** to improve the object classifier and thereby the safety and accuracy of the at least partial driving control of vehicle **300**.

[0058] FIG. **4** shows automotive control unit **400** configured to perform method **100**. automotive control unit **400** may include a processor **410**, a graphics processing unit (GPU) **420**, automotive processing system **430**, a memory **440**, a removable storage **450**, a storage **460**, a cellular interface **470**, a global navigation satellite system (GNSS) interface **480** and a communication interface **490**.

[0059] Processor **410** may be any kind of single-core or multi-core processing unit employing a reduced instruction set (RISC) or a complex instruction set (CISC). Exemplary RISC processing units include ARM based cores or RISC V based cores. Exemplary CISC processing units include x86 based cores or x86-64 based cores. Processor **410** may perform instructions causing automotive control unit **400** to perform method **100**. Processor **410** may be directly coupled to any of the components of computing device **400** or may be directly coupled to memory **430**, GPU **420** and a device bus.

[0060] GPU **420** may be any kind of processing unit optimized for processing graphics related instructions or more generally for parallel processing of instructions. As such, GPU **420** may be configured to generate a display of information, such as ADAS information or telemetry data, to a driver of the vehicle, e.g., via a head-up display (HUD) or a display arranged within the view of the driver. GPU **420**

may be coupled to the HUD and/or the display via connection **420**C. GPU **420** may further perform at least a part of method **100** to enable fast parallel processing of instructions relating to method **300**. It should be noted that in some embodiments, processor **410** may determine that GPU **320** need not perform instructions relating to method **100**. GPU **420** may be directly coupled to any of the components of automotive control unit **400** or may be directly coupled to processor **410** and memory **430**. In some embodiments, GPU **420** may also be coupled to the device bus.

[0061] Automotive processing system **430** may be any kind of system-on chip configured to provide trillions of operations per second (TOPS) to enable automotive control unit **300** to implement one or more ADAS while driving. Automotive processing system **430** may only interface with processor **410** or may interface with other devices via the system bus. Automotive processing system **430** may for example execute instructions relating to shared encoder **220**, instance decoder **230** and object class decoder **240**.

[0062] Memory **440** may be any kind of fast storage enabling processor **410**, GPU **420** and automotive processing system **430** to store instructions for fast retrieval during processing of instructions as well as to cache and buffer data. Memory **440** may be a unified memory coupled to processor **410** and GPU **420** and automotive processing system **430** to enable allocation of memory **440** to processor **410**, GPU **420** and automotive processing system **430** as needed. Alternatively, processor **410**, GPU **420** and automotive processing system **430** may be coupled to separate processor memory **440***a*, GPU memory **440***b* and automotive processing system memory **440***c*.

[0063] Removable storage **450** may be a storage device which can be removably coupled with automotive control unit **400**. Examples include a digital versatile disc (DVD), a compact disc (CD), a Universal Serial Bus (USB) storage device, such as an external SSD, or a magnetic tape. It should be noted that removable storage **350** may store data, such as instructions of method **100** and/or automotive sensor data **210**, or may be omitted.

[0064] Storage **460** may be a storage device enabling storage of program instructions and other data. For example, storage **460** may be a hard disk drive (HDD), a solid-state disk (SSD) or some other type of non-volatile memory. Storage **460** may for example store the instructions of method **100**.

[0065] Removable Storage **450** and storage **460** may be coupled to processor **410** via the system bus. The system bus may be any kind of bus system enabling processor **410** and optionally GPU **420** as well as automotive processing system **430** to communicate with the other devices of automotive control unit **400**. The system bus may for example be a Peripheral Component Interconnect express (PCIe) bus or a Serial AT Attachment (SATA) bus.

[0066] Cellular interface **470** may be any kind of interface enabling automotive control unit **400** to communicate via a cellular network, such as a 4G network or a 5G network.

[0067] GNSS interface **480** may be any kind of interface enabling automotive control unit **300** to receive position data provided by a satellite network, such as the Global Positioning System (GPS), the Global Navigation Satellite System (GLONASS) or Galileo.

[0068] Communications interface **490** may enable computing device **400** to interface with external devices, either directly or via network, via connection **380**C. Communications interface **380** may for example enable computing device **300** to couple to a wired or wireless network, such as Ethernet, Wifi, a Controller Area Network (CAN) bus or any bus system appropriate in vehicles. For example, automotive control unit **400** may be coupled to the one or more sensors **310** to receive information about the environment of vehicle **300** to classify objects in the vicinity of vehicle **300**. Communications interface **490** may also include a USB port or a serial port to enable direct communication with an external device.

[0069] Automotive control unit **400** may be integrated with the vehicle, e.g., beneath the cabin, under the dashboard or in the trunk of vehicle **400**.

[0070] The invention may further be illustrated by the following examples.

[0071] In an example, a method is configured to enable active learning for object classification in visual perception tasks in a vehicle configured to provide at least partial driving automation based on the object classification. The example method comprises determining, using an object classifier, for one or more data points within automotive sensor data, an object class out of a plurality of object classes. Each object class corresponds to an object type encounterable in a driving environment of the vehicle. The example method further comprises determining, for each of the one or more data points within the automotive sensor data, an uncertainty value based on a plurality of class probabilities and a confusion matrix. Each uncertainty value is indicative of an uncertainty of the object class determination. Each class probability is indicative, for each of the one or more data points, of the probability of each data point being indicative of a corresponding object class. The confusion matrix is indicative, for each object class of the plurality of object classes, of a probability of the object classifier determining, for a given object class, each of the object classes of the plurality of object classes. The example method further comprises determining an overall uncertainty of the automotive sensor data based on the uncertainty values of the one or more data points. The example method further comprises providing the automotive sensor data to an oracle if the overall uncertainty exceeds an overall uncertainty threshold. Finally, the example method comprises receiving, from the oracle, an object annotation of the automotive sensor data.

[0072] In the example method, the overall uncertainty threshold may correspond to a sum of an average overall uncertainty and at least one standard deviation of the average overall uncertainty.

[0073] In the example method, the plurality of class probabilities may correspond to a plurality of activation values of an output layer of the object classifier.

[0074] In the example method, the plurality of class probabilities may correspond to concentration parameters of a Dirichlet distribution.

[0075] In the example method, the determining the uncertainty value for each of the one or more data points may include calculating a modified plurality of class probabilities by multiplying the plurality of class probabilities with the confusion matrix.

[0076] In the example method, the determining the uncertainty value for each of the one or more data points may include calculating a transposed confusion matrix. The calculation of the transposed confusion matrix may comprise normalizing one of each row or each column of the confu-

sion matrix to generate a normalized confusion matrix and transposing the normalized confusion matrix to generate the transposed confusion matrix. Based on the transposed confusion matrix, the determining the uncertainty value may further comprise calculating a modified plurality of class probabilities by multiplying the plurality of class probabilities with the transposed confusion matrix.

[0077] In the example method, the determining the uncertainty value for each of the one or more data points may further include calculating, based on the modified plurality of class probabilities, each uncertainty value as one of an entropic uncertainty, a mean entropic uncertainty, a logarithmic uncertainty, or a mean logarithmic uncertainty.

[0078] In the example method, the determining the overall uncertainty of the automotive sensor data may include one of averaging all uncertainty values of the one or more data points of the automotive sensor data; averaging the sum of the uncertainty value and a false positive rate of the one or more data points of the automotive sensor data, wherein the false positive rate may correspond to a probability of a given object class being wrongly determined for a given data point divided by the sum of the probability of the given object class being wrongly determined for a given data point and a probability of the given object class being correctly not determined, averaging the square of all uncertainty values of the one or more data points of the automotive sensor data or selecting the highest uncertainty value of the uncertainty values as the overall uncertainty.

[0079] In the example method, the oracle may be a cloud-based object classification service.

[0080] In the example method, the oracle may be a user of the vehicle, and providing the automotive sensor data to the oracle may include displaying, on a display of the vehicle, the automotive sensor data.

[0081] In an example, an automotive control unit comprises at least one processing unit and a memory coupled to the at least one processing unit and configured to store exemplary machine-readable instructions. The exemplary machine-readable instructions cause the at least one processing unit to determine, using an object classifier, for one or more data points within automotive sensor data, an object class out of a plurality of object classes. Each object class corresponds to an object type encounterable in a driving environment of the vehicle. The exemplary machine-readable instructions further cause the at least one processing unit to determine, for the one or more data points within the automotive sensor data, an uncertainty value based on a plurality of class probabilities and a confusion matrix. Each uncertainty value is indicative of an uncertainty of the object class determination. Each class probability is indicative, for each of the one or more data points, of the probability of each data point belonging to a corresponding object class. The confusion matrix is indicative, for each object class of the plurality of object classes, of a probability of the object classifier determining, for a given object class, each of the object classes of the plurality of object classes. The exemplary machine-readable instructions further cause the at least one processing unit to determine an overall uncertainty of the automotive sensor data based on the uncertainty values of the one or more data points. The exemplary machine-readable instructions further cause the at least one processing unit to provide the automotive sensor data to an oracle if the overall uncertainty exceeds an overall uncertainty threshold. Finally, The exemplary machine-readable instructions further cause the at least one processing unit to receive, from the oracle, an object annotation of the automotive sensor data.

[0082] In the example automotive control unit, the machine-readable instructions may further cause the at least one processing unit to perform the method of any one of the above example methods.

[0083] In an example, a vehicle comprises the automotive control unit of any one of the above example automotive control units.

[0084] The preceding description has been provided to illustrate enabling active learning based on confusion matrix calibrated uncertainty for object classification in visual perception tasks in a vehicle. It should be understood that the description is in no way meant to limit the scope of the present disclosure to the precise embodiments discussed throughout the description. Rather, the person skilled in the art will be aware that the examples of the present disclosure may be combined, modified or condensed without departing from the scope of the present disclosure as defined by the following claims.

LIST OF REFERENCE SIGNS

[0085] **100-150** method and method steps
[0086] **210** automotive sensor data
[0087] **220** object classification encoder
[0088] **230** object classification decoder
[0089] **231** object class
[0090] **240** confusion matrix
[0091] **250** class probability modification
[0092] **260** Dirichlet distribution determination
[0093] **261** uncertainty value
[0094] **270** overall uncertainty estimation
[0095] **271** overall uncertainty
[0096] **280** oracle
[0097] **281** object annotation
[0098] **300** vehicle
[0099] **310** automotive sensor
[0100] **320** light
[0101] **400** automotive control unit
[0102] **410** CPU
[0103] **420** GPU
[0104] **420***c* connection
[0105] **430** automotive processing system
[0106] **440** memory
[0107] **450** removable storage
[0108] **460** storage
[0109] **470** cellular interface
[0110] **480** GNSS interface
[0111] **490** communications interface
[0112] α_1-α_k class probability

1. A method for enabling active learning for object classification in visual perception tasks in a vehicle that is configured to provide at least partial driving automation based on the object classification, the method comprising:

determining, using an object classifier, for one or more data points within automotive sensor data, an object class out of a plurality of object classes, the object class corresponding to an object type encounterable in a driving environment of the vehicle;

determining, for each of the one or more data points within the automotive sensor data, an uncertainty value based on a plurality of class probabilities and a confusion matrix, wherein:

the uncertainty value is indicative of an uncertainty of an object class determination,

each of the class probabilities is indicative, for each of the one or more data points, of a probability of each data point being indicative of a corresponding object class, and

the confusion matrix is indicative, for each object class of the plurality of object classes, of a probability of the object classifier determining, for a given object class, each of the plurality of object classes;

determining an overall uncertainty of the automotive sensor data based on the uncertainty values of the one or more data points;

determining whether the overall uncertainty exceeds an overall uncertainty threshold, and providing the automotive sensor data to an oracle if the overall uncertainty exceeds the overall uncertainty threshold; and

receiving, from the oracle, an object annotation of the automotive sensor data.

2. The method according to claim **1**, wherein the overall uncertainty threshold corresponds to a sum of an average overall uncertainty and at least one standard deviation of the average overall uncertainty.

3. The method according to claim **1**, wherein the plurality of class probabilities corresponds to a plurality of activation values of an output layer of the object classifier.

4. The method according to claim **2**, wherein the plurality of class probabilities corresponds to a plurality of activation values of an output layer of the object classifier.

5. The method according to claim **1**, wherein the plurality of class probabilities corresponds to concentration parameters of a Dirichlet distribution.

6. The method according to claim **2**, wherein the plurality of class probabilities corresponds to concentration parameters of a Dirichlet distribution.

7. The method according to claim **1**, wherein the determining the uncertainty value for each of the one or more data points includes calculating a modified plurality of class probabilities by multiplying the plurality of class probabilities with the confusion matrix.

8. The method according to claim **2**, wherein the determining the uncertainty value for each of the one or more data points includes calculating a modified plurality of class probabilities by multiplying the plurality of class probabilities with the confusion matrix.

9. The method according to claim **1**, wherein the determining the uncertainty value for each of the one or more data points includes calculating a transposed confusion matrix, comprising:

normalizing one of each row or each column of the confusion matrix to generate a normalized confusion matrix; and

transposing the normalized confusion matrix to generate the transposed confusion matrix; and

calculating a modified plurality of class probabilities by multiplying the plurality of class probabilities with the transposed confusion matrix.

10. The method according to claim **2**, wherein the determining the uncertainty value for each of the one or more data points includes calculating a transposed confusion matrix, comprising:

normalizing one of each row or each column of the confusion matrix to generate a normalized confusion matrix; and

transposing the normalized confusion matrix to generate the transposed confusion matrix; and

calculating a modified plurality of class probabilities by multiplying the plurality of class probabilities with the transposed confusion matrix.

11. The method according to claim **7**, wherein the determining the uncertainty value for each of the one or more data points further includes calculating, based on the modified plurality of class probabilities, each uncertainty value as one of:

an entropic uncertainty,

a mean entropic uncertainty,

a logarithmic uncertainty, or

a mean logarithmic uncertainty.

12. The method according to claim **9**, wherein the determining the uncertainty value for each of the one or more data points further includes calculating, based on the modified plurality of class probabilities, each uncertainty value as one of:

an entropic uncertainty,

a mean entropic uncertainty,

a logarithmic uncertainty, or

a mean logarithmic uncertainty.

13. The method according to claim **1**, wherein the determining the overall uncertainty of the automotive sensor data includes one of:

averaging all uncertainty values of the one or more data points of the automotive sensor data,

averaging a sum of the uncertainty value and a false positive rate of the one or more data points of the automotive sensor data, wherein the false positive rate corresponds to a probability of a given object class being wrongly determined for a given data point divided by the sum of the probability of the given object class being wrongly determined for a given data point and a probability of the given object class being determined incorrectly,

averaging the square of all uncertainty values of the one or more data points of the automotive sensor data, or

selecting the highest uncertainty value of the uncertainty values as the overall uncertainty.

14. The method according to claim **1**, wherein the oracle is a cloud-based object classification service.

15. The method according to claim **1**, wherein:

the oracle is a user of the vehicle, and

providing the automotive sensor data to the oracle includes displaying, on a display of the vehicle, the automotive sensor data.

16. An automotive control apparatus comprising:

at least one processing unit; and

a memory coupled to the at least one processing unit and configured to store machine-readable instructions, wherein the machine-readable instructions cause the at least one processing unit to:

determine, using an object classifier, for one or more data points within automotive sensor data, an object class out of a plurality of object classes, each object class corresponding to an object type encounterable in a driving environment of the vehicle;

determine, for each of the one or more data points within the automotive sensor data, an uncertainty value based on a plurality of class probabilities and a confusion matrix, wherein:

each uncertainty value is indicative of an uncertainty of an object class determination,

each class probability is indicative, for each of the one or more data points, of a probability of each data point being indicative of a corresponding object class, and

the confusion matrix is indicative, for each object class of the plurality of object classes, of a probability of the object classifier determining, for a given object class, each of the object classes of the plurality of object classes;

determine an overall uncertainty of the automotive sensor data based on the uncertainty values of the one or more data points;

determine whether the overall uncertainty exceeds an overall uncertainty threshold, and provide the automotive sensor data to an oracle if the overall uncertainty exceeds the overall uncertainty threshold; and

receive, from the oracle, an object annotation of the automotive sensor data.

17. The automotive control apparatus according to claim **16**, wherein the overall uncertainty threshold corresponds to a sum of an average overall uncertainty and at least one standard deviation of the average overall uncertainty.

18. A vehicle comprising the automotive control apparatus according to claim **16**.

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