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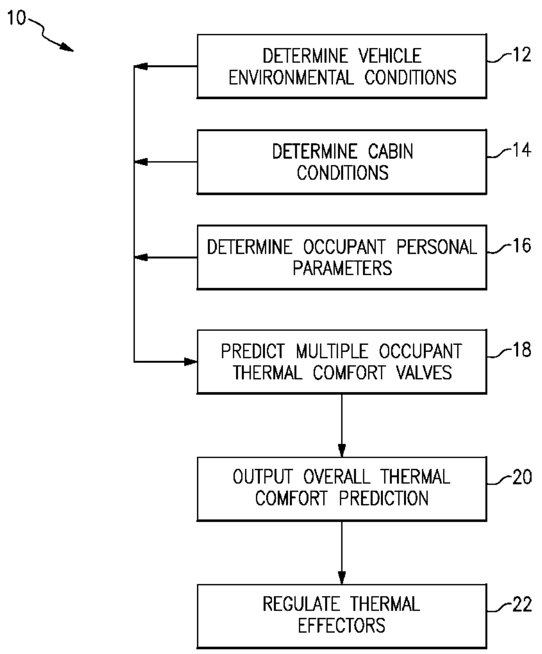
(54) **Title:** METHOD AND SYSTEM USING MACHINE LEARNING ALGORITHM FOR CONTROLLING THERMAL COMFORT

FIG.3



(57) **Abstract:** A method (10) of controlling an occupant microclimate system includes determining vehicle environmental conditions (Block 12), determining occupant personal parameters (Block 16), determining cabin conditions (Block 14), predicting a probability of comfort at a first portion and second portion of an occupant based upon the environmental conditions, cabin conditions, and occupant personal parameters, combining the predicted probabilities of comfort with the vehicle environmental conditions and the occupant personal parameters according to a relationship determined by the one of the machine learned algorithm and the machine learning algorithm, outputting at least one of a binary thermal comfort determination and a probability of overall thermal comfort, and regulating at least one thermal effector based upon the one of the binary thermal comfort determination (Block 20) and the probability of overall thermal comfort (Block 22). The predicting step is performed using one of a machine learned algorithm and a machine learning algorithm.

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METHOD AND SYSTEM USING MACHINE LEARNING ALGORITHM FOR CONTROLLING THERMAL COMFORT

RELATED APPLICATION

[0001] This application also incorporates by reference the application entitled "Occupant Clothing Predicter For Thermal Effector Control" which has serial number 63/007,047 and was filed herewith on April 8, 2020 and the application entitled "Machine Learning Algorithm for Controlling Thermal Comfort" which has a serial number 63/012,335.

[0002] This application claims priority to United States Provisional Patent Application No. 63/068059 filed on August 20, 2020.

BACKGROUND

[0001] Vehicles commonly include heating, ventilation and air conditioning (HVAC) systems to thermally condition air within the vehicle's cabin. A typical modern vehicle also includes seats having thermal effectors that are controlled to achieve occupant thermal comfort. The thermal effectors may include heating and/or cooling elements that further heat or cool the occupant through the seat support surfaces.

[0002] Although many systems have been proposed, it is difficult to achieve a commercial seating thermal control system that effectively and efficiently achieves occupant thermal comfort using the seat, particularly for the numerous variable conditions present in a vehicle cabin.

[0003] Thermal comfort is usually associated with one simple parameter such as the mean temperature. Although temperature is a major driver of thermal comfort it does a poor job in reflecting the perception of pleasantness/unpleasantness in people. This perception is a regulated by multiple environmental parameters on one hand (temperature stratification, humidity, and radiation) and personal characteristics on the other (clothing level, height, weight, age, gender etc). Therefore, the driver of an automobile has to frequently regulate HVAC controls to account for the dynamic environment of the car cabin. The problem is aggravated in case of multiple occupancy where multiple opinions come at play.

[0004] Better approximations to the problem of thermal comfort in a car cabin have been implemented with the most notable being the equivalent homogenous temperature (EHT). EHT is a better measure of the environmental factors in the cabin. However, it does not address the component of personal characteristics and preferences. Other attempts to solve the problem rely on expensive solutions such as dedicated infra-red thermal cameras to estimate skin temperature.

SUMMARY

[0005] An exemplary method of controlling an occupant microclimate system, the method comprising the steps of determining vehicle environmental conditions, determining occupant personal parameters, determining cabin conditions, predicting a probability of comfort at a first portion of an occupant and a probability of comfort at a second portion of the occupant based upon the environmental conditions, cabin conditions, and occupant personal parameters, the predicting step performed using one of a machine learned algorithm and a machine learning algorithm, combining the predicted probability of comfort at the first portion and the probability of comfort at the second portion with the vehicle environmental conditions and the occupant personal parameters according to a relationship determined by the one of the machine learned algorithm and the machine learning algorithm, outputting at least one of a binary thermal comfort determination and a probability of overall thermal comfort, and regulating at least one thermal effector based upon the one of the binary thermal comfort determination and the probability of overall thermal comfort.

[0006] In another example of the above described method of controlling an occupant microclimate system the vehicle environmental conditions include at least one of vehicle exterior temperature and vehicle exterior humidity.

[0007] In another example of any of the above described methods of controlling an occupant microclimate system the cabin conditions include at least two of a cabin temperature data, a cabin humidity and a cabin solar radiation.

[0008] In another example of any of the above described methods of controlling an occupant microclimate system the cabin conditions include at least three of mean temperature at the cabin floor, mean temperature at the occupant belt line or waist, mean temperature at a breath level or face, temperature of a cushion between knees at a surface of the cushion, an internal NTC temperature of the cushion, a temperature of a seat back at a surface of the seat back, and internal NTC temperature of the seat back, and a difference between the temperatures at the breath level and at a cabin floor.

[0009] In another example of any of the above described methods of controlling an occupant microclimate system the occupant personal parameters include at least two of occupant weight, occupant height, occupant gender, and occupant clothing.

[0010] In another example of any of the above described methods of controlling an occupant microclimate system the one of the machine learned algorithm and the machine learning algorithm is an Extremely Gradient Boosted Trees (XGBoost) machine learned system.

[0011] In another example of any of the above described methods of controlling an occupant microclimate system combining the predicted probability of comfort at the first portion and the probability of comfort at the second portion with the vehicle environmental conditions and the occupant personal parameters further includes at least one additional predicted probability of a comfort parameter.

[0012] In another example of any of the above described methods of controlling an occupant microclimate system the at least one additional predicted probability of comfort parameter has a lower weight in the combination than the predicted probability of comfort at the first portion and the probability of comfort at the second portion.

[0013] In another example of any of the above described methods of controlling an occupant microclimate system the thermal effectors are selected from the group comprising a climate-controlled seat, a head rest/neck conditioner, a climate-controlled headliner, a steering wheel, a heated gear shifter, a heater mat, and a mini-compressor system.

[0014] Another example of any of the above described methods of controlling an occupant microclimate system further includes predicting a probability of comfort at a third portion of the occupant based upon the environmental conditions, cabin temperature data, and occupant personal parameters, and wherein combining the predicted probability of comfort at the first portion and the probability of comfort at the second portion includes combining the predicted probability of comfort at the third portion.

[0015] In another example of any of the above described methods of controlling an occupant microclimate system the third portion is a portion of the occupant contacting a steering wheel.

[0016] In another example of any of the above described methods of controlling an occupant microclimate system the first portion is a portion of the occupant contacting a seat cushion and the second portion is a portion of the occupant contacting a seat back.

[0017] Another example of any of the above described methods of controlling an occupant microclimate system further includes predicting a probability of a whole-body comfort of the occupant based upon the environmental conditions, cabin temperature data, and occupant personal parameters, and wherein combining the predicted probability of comfort at the first portion and the probability of comfort at the second portion includes combining the probability of the whole-body comfort.

[0018] In another example of any of the above described methods of controlling an occupant microclimate system combining the predicted probability of comfort at the first portion, the probability of comfort at the second portion, and the probability of the whole-body comfort further includes providing the probabilities and the environmental conditions, the cabin conditions, and the occupant personal parameters to a deep learning multi output (DLMO) function and combining using the DLMO function.

[0019] In one exemplary embodiment a microclimate control system for an occupant includes a first input device configured to provide vehicle environmental conditions, a second input device configured to provide occupant personal parameters, a third input device configured to provide cabin conditions, at least one thermal effector configured to heat and/or cool an occupant, and a controller configured to predict a probability of comfort at a first position and a probability of comfort at a second position of at least one person based upon the environmental conditions, cabin conditions, and occupant personal parameters, the predicting step performed using one of a machine learning algorithm and a machine learned algorithm, combine the predicted probability of comfort at the first position and the probability of comfort at the second position with the vehicle environmental conditions and the occupant personal parameters according to a relationship determined by the one of the machine learned algorithm and the machine learning algorithm, outputting at least one of a binary thermal comfort determination and a probability of overall thermal comfort, and regulating at least one thermal effector based upon the one of the binary thermal comfort determination and the probability of overall thermal comfort.

[0020] In another example of the above described microclimate control system for an occupant the vehicle environmental conditions include at least one of vehicle exterior temperature and vehicle exterior humidity.

[0021] In another example of any of the above described microclimate control systems for an occupant the cabin conditions include at least two of a cabin temperature data, a cabin humidity and a cabin solar radiation.

[0022] In another example of any of the above described microclimate control systems for an occupant the cabin conditions include at least three of mean temperature at the cabin floor, mean temperature at the occupant belt line or waist, mean temperature at a breath level or face, temperature of a cushion between knees at a surface of a cushion, an internal NTC temperature of the cushion, a temperature of a seat back at a surface of the seat back, and internal NTC temperature of the seat back, and a difference between the temperatures at the breath level and at a cabin floor.

[0023] In another example of any of the above described microclimate control systems for an occupant the second input device is at least one array of pressure sensors in a seat, and the occupant personal parameters include at least two of occupant weight, occupant height, occupant gender, and occupant clothing.

[0024] In another example of any of the above described microclimate control systems for an occupant combining the predicted probability of comfort at the first position and the predicted probability of comfort at the second position with the vehicle environmental conditions and the occupant personal parameters further includes at least one additional predicted probability of a comfort parameter.

[0025] In another example of any of the above described microclimate control systems for an occupant the at least one additional predicted probability of comfort parameter has a lower weight in the combination than the predicted probability of comfort at the first position and the probability of comfort at the second position.

[0026] Another example of any of the above described microclimate control systems for an occupant further includes predicting a probability of a whole-body comfort of the occupant based upon the environmental conditions, cabin temperature data, and occupant personal parameters, and wherein combining the predicted probability of comfort at the first portion and the probability of comfort at the second portion includes combining the probability of the whole-body comfort.

[0027] In another example of any of the above described microclimate control systems for an occupant combining the predicted probability of comfort at the first portion, the probability of comfort at the second portion, and the probability of the whole-body comfort further includes providing the probabilities and the environmental conditions, the cabin conditions, and the occupant personal parameters to a deep learning multi output (DLMO) function and combining using the DLMO function.

BRIEF DESCRIPTION OF THE DRAWINGS

[0028] The disclosure can be further understood by reference to the following detailed description when considered in connection with the accompanying drawings wherein:

[0029] Figure 1 is a block diagram of a neural network using inputs affecting occupant thermal comfort to establish a mapping between those inputs and an occupant thermal comfort output.

[0030] Figure 2 is a simplified block diagram illustrating neural network training using the inputs illustrating in Figure 1 to establish the mapping between the inputs and output.

[0031] Figure 3 is a flow chart depicting an example method of controlling an occupant microclimate system.

[0032] Figure 4 illustrates an exemplary system for effecting thermal controls within a vehicle.

[0033] Figure 5 schematically illustrates an alternate presentation of the system of Figures 1-3, with an added probability of whole-body comfort estimation.

[0034] The embodiments, examples and alternatives of the preceding paragraphs, the claims, or the following description and drawings, including any of their various aspects or respective individual features, may be taken independently or in any combination. Features described in connection with one embodiment are applicable to all embodiments, unless such features are incompatible.

DETAILED DESCRIPTION

[0035] This disclosure provides a method for capturing environmental and personal characteristics and making predictions of individual preferences of thermal satisfaction within the car cabin.

[0036] The disclosed system and method rely upon the readings from a grid of simple, inexpensive sensors, or inputs, and the output of transfer functions, where such sensors are lacking, to infer the thermal comfort state of one or more automobile passenger(s) according to a relationship f(x). The prediction is based on a single machine learning algorithm, which is trained using a data set of the inputs and their associated occupant thermal comfort. The machine learning algorithm may predict a different occupant thermal comfort for each person in the vehicle and the thermal effectors are controlled accordingly. The algorithm used in the prediction of thermal comfort is very flexible in expanding to include other signals, such as heart rate variability parameters, and to make inferences or decisions on wellness preferences, and can be adapted by one skilled in the art to accommodate any other newly available input signal types.

[0037] Figure 1 is a highly simplified block diagram of a neural network. The neural network (f( )) performs a non-linear multivariate mapping from one set of parameters (inputs 200) to another (outputs 300). The outputs 300 are determined via a function (or set of functions) f(x) that is the result of the mapping performed on the inputs by the neural network. In one disclosed embodiment, inputs that affect occupant thermal comfort are mapped by the neural network (f( )) to provide an output corresponding to occupant thermal comfort. Inputs include, for example, estimated external temperature taken from the CAN bus of the vehicle 201, occupant weight 202, occupant height 203, occupant gender 204, mean air temperature at the cabin floor 205, mean air temperature at the occupant belt line or waist 206, mean air temperature at the breath level or face 207, air temperature measured at the cushion between the knees 208, temperature of the exterior surface of the seat back 209, internal NTC temperature of the seat back 211, temperature of the exterior surface of the seat cushion 210, internal NTC temperature of the cushion 212, cabin humidity 213, cabin solar radiation 214, and an on/off status of a heated steering wheel 215. In alternative embodiments, additional or different inputs may be used.

[0038] By using the internal NTC temperature of the seat back 211 and of the cushion 212 combined with the exterior surface temperatures of the same, the actual temperature gradient from the internal heating element to the seat surface is determined. This allows the process to account for any thermal gradients that may differ from default gradients due to the compression from the person sitting on the seat, wear on the system, or any similar factor. This modification to the thermal gradient is dependent not only on the weight of the person, but also on how the person carries their weight, where in the seat the person is positioned, how worn the cushion is, and the like. The determined temperature transfer gradient allows the relationship f(x) to account for the actual speed at which the heat from the thermal effectors (see Figure 4) within the cushions and seat back reaches the person, which further impacts the comfort of the person.

[0039] The relationship f(x) utilizes the inputs 200 to determine an output 300 that is one of a binary thermal comfort prediction 301 or a probability of thermal comfort 302 using a multi-step process. The first step 400 receives the inputs 200 and generates a clothing insulation prediction 401 based on the estimated external temperature taken from the CAN bus of the vehicle

201, occupant weight 202, occupant height 203, and the occupant gender 204. In addition, the first step estimates a temperature gradient 402 from the floor to a person's head using the mean air temperature at the cabin floor 205, mean air temperature at the occupant belt line or waist 206, mean air temperature at the breath level or face 207, air temperature measured at the cushion between the knees 208.

[0040] The estimates 401, 402 are determined in the first step 400 and the inputs 200 are then used in a second step 500 to estimate a probability of comfort at the cushion 501, a probability of comfort at the back 502, and a probability of comfort at the hands 503 of the person. Each of these probabilities is determined via a unique relationship generated by the single neural network during the neural network training process. While it is appreciated that comfort at the cushion, back and hands has the largest impact on a person's overall comfort or discomfort, in alternative examples additional comfort locations (e.g. comfort at the body, comfort at the feet, a whole-body comfort metric, etc.) can be determined and utilized alongside the cushion, back and hands determinations. In such examples, the additional comfort determinations can be given a smaller weight in determining the output 300 for the overall comfort determination.

[0041] The output 300 takes the form of either a binary thermal comfort 301 output or a probability of thermal comfort 302 output depending on the configuration of the system. The binary thermal comfort 301 output is a binary prediction of either "comfort" or "discomfort" and indicates whether the person is thermally comfortable or uncomfortable. The probability of thermal comfort 302 output is a prediction of a probability that the person is comfortable. Utilization of the probability of thermal comfort can allow for further improvement of some systems by providing a targeted minimum probability of comfort and adjusting controls until the minimum probability is met.

[0042] The determinations made in the first step 400 and the second step 500 are made according to the relationship (f(x)) that is determined via the machine learning algorithm. While described herein using a machine learning algorithm that continuously iterates and develops, it is appreciated that alternative examples can utilize an algorithm that is learned via a machine learning process but remains static once implemented. Such a system is referred to as a machine learned algorithm. In one example, the machine learning system utilized is an Extreme Gradient Boost (XGBoost) system. It is appreciated that in alternative examples, alternative machine learning systems can be used to similar effect.

[0043] In order to determine the relationship f(x) between the inputs and an occupant thermal comfort (the output 300) for the machine learning algorithm being utilized (e.g. XGBoost), the machine learning algorithm is trained using a data set. Referring to Figure 2, the training 100 begins by providing a segment of a large data record for training purposes, indicated at block 102. An algorithm is iteratively trained to a desired error (block 106), using additional data from the training data set (block 108), if necessary. Once the error goal is achieved, the training is complete (block 110) and the machine learning algorithm relationship f(x) has been sufficiently established for use in the vehicle climate control system.

[0044] After the neural net has been trained using a data set, the predicted relationship between the inputs and output for the given machine learning algorithm is established. This training process is performed using a single machine learning algorithm to increase the speed at which the output 300 is determined, while the utilization of the predicted probability of cushion comfort 501, probability of back comfort 502 and probability of hand comfort 503 is heavily weighted to improve the accuracy of the output 300.

[0045] In one example disclosed method 10 shown in Figure 3, vehicle environmental conditions are determined, as indicated at block 12. The vehicle environmental conditions include, for example, vehicle exterior temperature and vehicle exterior humidity. Cabin conditions are also determined, as indicated at block 14. The cabin conditions include at least one of cabin temperature data, cabin humidity and cabin solar radiation. Occupant personal parameters are determined, as indicated at block 16. Occupant personal parameters include, for example, occupant weight, occupant height and occupant gender, occupant age, occupant culture/region and/or occupant habit(s). These parameters may be sensed directly or indirectly, input manually or automatically from external devices (e.g., phones, watches or fitness trackers), or predicted using one or more algorithms.

[0046] The thermal comfort control method 10 utilizes the data provided from blocks 12, 14 and 16 to predict a multiple of occupant thermal comfort values of each occupant at the cushion, at the back and at the hands of the occupant, as indicated at block 18. The prediction is performed using a single machine learning algorithm to provide the multiple occupant thermal comfort values. Example machine learning algorithms that can be used as an alternative to XGBoost include LightGBM, Neural Nets, Random Forests, Extremely Randomized Trees, Adaptive boosting, Logistic Regression, Support Vector Machines, and/or Naive Bayes classifiers.

[0047] The multiple occupant thermal comfort values 501, 502, 503 are combined with the inputs 200 in the second step 500 according to the relationship f(x) to determine an overall thermal comfort prediction output 300 at block 20. The overall thermal comfort prediction output 300 is, in one example, a binary comfort or discomfort determination. The output 300 is provided to a controller that regulates a set of thermal effectors to create the defined conditions at block 22 to maintain the output.

[0048] In other examples, the overall thermal comfort prediction output 300 is a probability of thermal comfort 302. In examples, where the overall thermal comfort prediction output 300 is a probability of thermal comfort, the method 10 includes a "probability threshold". When the determined probability of thermal comfort meets or exceed the threshold, the method 10 outputs the settings to the controller that regulates the thermal effectors, as described in the binary comfort/discomfort output 301. Alternatively, when the probability of comfort is below the threshold, the method 10 can alter one or more parameters that defines the inputs and reiterate the method 10 the determine the new probability of comfort.

[0049] With continued reference to Figures 1-3, and with like numerals indicating like elements, Figure 5 schematically illustrates an alternate example presentation the system of Figures 1-3, with an added consideration of the probability of whole-body comfort estimation 504. The example of figure 5 operates substantially identically to the examples of Figures 1-3 to generate predictions of the probability of local comfort at the hands, back and cushion using prediction models 501, 052, 503. In addition to the local comfort prediction models, the system of Figure 5 includes an estimation model 504 that estimates a probability of whole-body comfort using the f(x) relationship(s) described previously. This estimation is then stacked with each of the outputs from the local prediction estimation models 501, 502, 503 on top of the rest of the inputs and provided to a deep learning architecture (DLMO 601) that generates multiple outputs.

[0050] The deep learning architecture accepts the stacked combination of each of the estimated probabilities from the estimation models 501, 502, 503, 504 and the inputs 201-215 to generate multiple outputs with one output corresponding to the binary thermal comfort proposition 301, and another output corresponding to probability of overall thermal comfort. The multiple output deep learning algorithm is referred to as DLMO 601, and provides a prediction of the overall thermal comfort while at the same time optimizing predictions for each of the local body comforts.

[0051] An example system for implementing comfort controls based on the above described method 600 illustrated in Figure 4. The example system includes a processor 630 that is configured to implement the relationships f(x) determined by the neural network 630 and generate the output(s) 300 described above. The outputs are provided to a thermal effector controller 640. The estimated occupant thermal comfort from the output 300 is then used by the thermal effector controller 640 to regulate the thermal effectors 602, 604, 606, 608, 610, 612, 614, 612 within the vehicle. The thermal effectors include, for example, the seat 602, a steering wheel 604, a shifter 606, a mat 608 (such as a floor mat, a door panel, and/or a dash panel), a headliner 610, a mini-compressor system 612, a cushion thermal conditioner 614, and/or a back/neck/head thermal conditioner 616.

[0052] One example thermal comfort model relies upon an equivalent homogeneous temperature (EHT) to control the system. EHT represents the total thermal effects on an occupant as a measure of the occupant's heat loss, which produces a whole-body thermal sensation. EHT takes into account the combined convective, conductive and radiative effects on the occupant and combines these effects into a single value, which is especially useful for modelling non-uniform thermal environments.

[0053] One example calculation of EHT can be found in Han, Taeyoung and Huang, Linjie, "A Model for Relating a Thermal Comfort Scale to EHT Comfort Index," SAE Technical Paper 2004-01-0919, 2004. As explained in this SAE paper, which is incorporated by reference in its entirety, the modeled thermal environment is affected by “breath” air temperature, mean radiant temperature (MRT), air velocity, solar load and relative humidity. This application hereby incorporated by reference the co-pending provisional applications entitled “Automotive Seat Based Microclimate System” which has a serial number of 62/937,890 and was filed on November 20, 2019 and “Thermophysiologically-Based Microclimate Control System” which has a serial number of 62/970,409 and was filed on February 5, 2020.

[0054] In order to increase the accuracy of the predicted thermal comfort, as well as the speed by which the EHT analysis processes the inputs 200 to determine the predictions, in one example the predicted cushion, back, and hand probability of comfort 501, 502, 503 are provided with heavier weighting than other parameters as these portions of the person represent the dominant feeling of comfort for the person.

[0055] The occupant temperature stratification may be calculated using transfer functions based upon empirical data. In the example, the occupant temperature stratification approximates the temperature at six different heights relative to the seated occupant. That is, the temperature vertical stratification adjusts the cabin air temperature for the level of stratification in that particular zone e.g. “breath level”.

[0056] It should also be understood that although a particular component arrangement is disclosed in the illustrated embodiment, other arrangements will benefit herefrom. Although particular step sequences are shown, described, and claimed, it should be understood that steps may be performed in any order, separated or combined unless otherwise indicated and will still benefit from the present invention.

[0057] Although the different examples have specific components shown in the illustrations, embodiments of this invention are not limited to those particular combinations. It is possible to use some of the components or features from one of the examples in combination with features or components from another one of the examples.

[0058] Although an example embodiment has been disclosed, a worker of ordinary skill in this art would recognize that certain modifications would come within the scope of the claims. For that reason, the following claims should be studied to determine their true scope and content.

CLAIMS

What is claimed is:

1. A method of controlling an occupant microclimate system, the method comprising the steps of:

determining vehicle environmental conditions;

determining occupant personal parameters;

determining cabin conditions;

predicting a probability of comfort at a first portion of an occupant and a probability of comfort at a second portion of the occupant based upon the environmental conditions, cabin conditions, and occupant personal parameters, the predicting step performed using one of a machine learned algorithm and a machine learning algorithm;

combining the predicted probability of comfort at the first portion and the probability of comfort at the second portion with the vehicle environmental conditions and the occupant personal parameters according to a relationship determined by the one of the machine learned algorithm and the machine learning algorithm;

outputting at least one of a binary thermal comfort determination and a probability of overall thermal comfort; and

regulating at least one thermal effector based upon the one of the binary thermal comfort determination and the probability of overall thermal comfort.

2. The method of claim 1, wherein the vehicle environmental conditions include at least one of vehicle exterior temperature and vehicle exterior humidity.

3. The method of claim 1, wherein the cabin conditions include at least two of a cabin temperature data, a cabin humidity and a cabin solar radiation.

4. The method of claim 3, wherein the cabin conditions include at least three of mean temperature at the cabin floor, mean temperature at the occupant belt line or waist, mean

temperature at a breath level or face, temperature of a cushion between knees at a surface of the cushion, an internal NTC temperature of the cushion, a temperature of a seat back at a surface of the seat back, and internal NTC temperature of the seat back, and a difference between the temperatures at the breath level and at a cabin floor.

5. The method of claim 1, wherein the occupant personal parameters include at least two of occupant weight, occupant height, occupant gender, and occupant clothing.

6. The method of claim 1, wherein the one of the machine learned algorithm and the machine learning algorithm is an Extremely Gradient Boosted Trees (XGBoost) machine learned system.

7. The method of claim 1, wherein combining the predicted probability of comfort at the first portion and the probability of comfort at the second portion with the vehicle environmental conditions and the occupant personal parameters further includes at least one additional predicted probability of a comfort parameter.

8. The method of claim 7, wherein the at least one additional predicted probability of comfort parameter has a lower weight in the combination than the predicted probability of comfort at the first portion and the probability of comfort at the second portion.

9. The method of claim 1, wherein the thermal effectors are selected from the group comprising a climate-controlled seat, a head rest/neck conditioner, a climate-controlled headliner, a steering wheel, a heated gear shifter, a heater mat, and a mini-compressor system.

10. The method of claim 1, further comprising predicting a probability of comfort at a third portion of the occupant based upon the environmental conditions, cabin temperature data, and occupant personal parameters, and wherein combining the predicted probability of comfort at

the first portion and the probability of comfort at the second portion includes combining the predicted probability of comfort at the third portion.

11. The method of claim 10, wherein the third portion is a portion of the occupant contacting a steering wheel.

12. The method of claim 1, wherein the first portion is a portion of the occupant contacting a seat cushion and the second portion is a portion of the occupant contacting a seat back.

13. The method of claim 1, further comprising predicting a probability of a whole-body comfort of the occupant based upon the environmental conditions, cabin temperature data, and occupant personal parameters, and wherein combining the predicted probability of comfort at the first portion and the probability of comfort at the second portion includes combining the probability of the whole-body comfort.

14. The method of claim 13, wherein combining the predicted probability of comfort at the first portion, the probability of comfort at the second portion, and the probability of the whole-body comfort further includes providing the probabilities and the environmental conditions, the cabin conditions, and the occupant personal parameters to a deep learning multi output (DLMO) function and combining using the DLMO function.

15. A microclimate control system for an occupant, comprising:

a first input device configured to provide vehicle environmental conditions;

a second input device configured to provide occupant personal parameters;

a third input device configured to provide cabin conditions;

at least one thermal effector configured to heat and/or cool an occupant; and

a controller configured to predict a probability of comfort at a first position and a probability of comfort at a second position of at least one person based upon the environmental conditions, cabin conditions, and occupant personal parameters, the predicting step performed using one of a machine learning algorithm and a machine learned algorithm, combine the predicted probability of comfort at the first position and the probability of comfort at the second position with the vehicle environmental conditions and the occupant personal parameters according to a relationship determined by the one of the machine learned algorithm and the machine learning algorithm, outputting at least one of a binary thermal comfort determination and a probability of overall thermal comfort, and regulating at least one thermal effector based upon the one of the binary thermal comfort determination and the probability of overall thermal comfort.

16. The system of claim 15, wherein the vehicle environmental conditions include at least one of vehicle exterior temperature and vehicle exterior humidity.

17. The system of claim 15, wherein the cabin conditions include at least two of a cabin temperature data, a cabin humidity and a cabin solar radiation.

18. The system of claim 17, wherein the cabin conditions include at least three of mean temperature at the cabin floor, mean temperature at the occupant belt line or waist, mean temperature at a breath level or face, temperature of a cushion between knees at a surface of a cushion, an internal NTC temperature of the cushion, a temperature of a seat back at a surface of the seat back, and internal NTC temperature of the seat back, and a difference between the temperatures at the breath level and at a cabin floor.

19. The system of claim 15, wherein the second input device is at least one array of pressure sensors in a seat, and the occupant personal parameters include at least two of occupant weight, occupant height, occupant gender, and occupant clothing.

20. The system of claim 15, wherein combining the predicted probability of comfort at the first position and the predicted probability of comfort at the second position with the vehicle

environmental conditions and the occupant personal parameters further includes at least one additional predicted probability of a comfort parameter.

21. The system of claim 19, wherein the at least one additional predicted probability of comfort parameter has a lower weight in the combination than the predicted probability of comfort at the first position and the probability of comfort at the second position.

22. The method of claim 1, further comprising predicting a probability of a whole-body comfort of the occupant based upon the environmental conditions, cabin temperature data, and occupant personal parameters, and wherein combining the predicted probability of comfort at the first portion and the probability of comfort at the second portion includes combining the probability of the whole-body comfort.

23. The method of claim 13, wherein combining the predicted probability of comfort at the first portion, the probability of comfort at the second portion, and the probability of the whole-body comfort further includes providing the probabilities and the environmental conditions, the cabin conditions, and the occupant personal parameters to a deep learning multi output (DLMO) function and combining using the DLMO function.

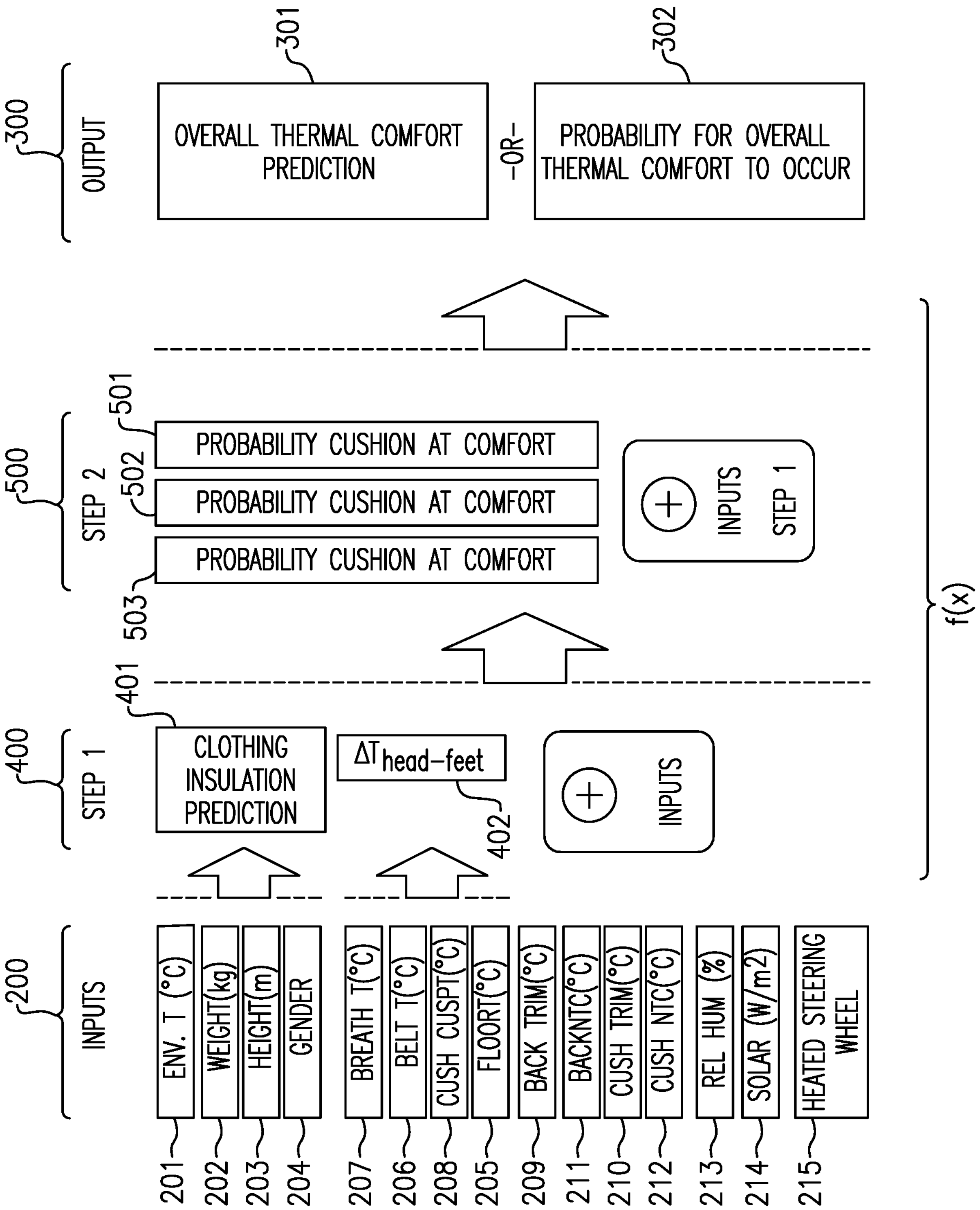
OUTPUT
300
OVERALL THERMAL COMFORT PREDICTION
301
-OR-
PROBABILITY FOR OVERALL THERMAL COMFORT TO OCCUR
302
STEP 2
500
PROBABILITY CUSHION AT COMFORT
501
PROBABILITY CUSHION AT COMFORT
502
PROBABILITY CUSHION AT COMFORT
503
INPUTS
STEP 1
f(x)
STEP 1
400
CLOTHING INSULATION PREDICTION
401
ΔT head-feet
402
INPUTS
INPUTS
200
ENV. T (°C)
201
WEIGHT(kg)
202
HEIGHT(m)
203
GENDER
204
BREATH T(°C)
207
BELT T(°C)
206
CUSH CUSPT(°C)
208
FLOORT(°C)
205
BACK TRIM(°C)
209
BACKNTC(°C)
211
CUSH TRIM(°C)
210
CUSH NTC(°C)
212
REL HUM (%)
213
SOLAR (W/m2)
214
HEATED STEERING WHEEL
215

FIG.1

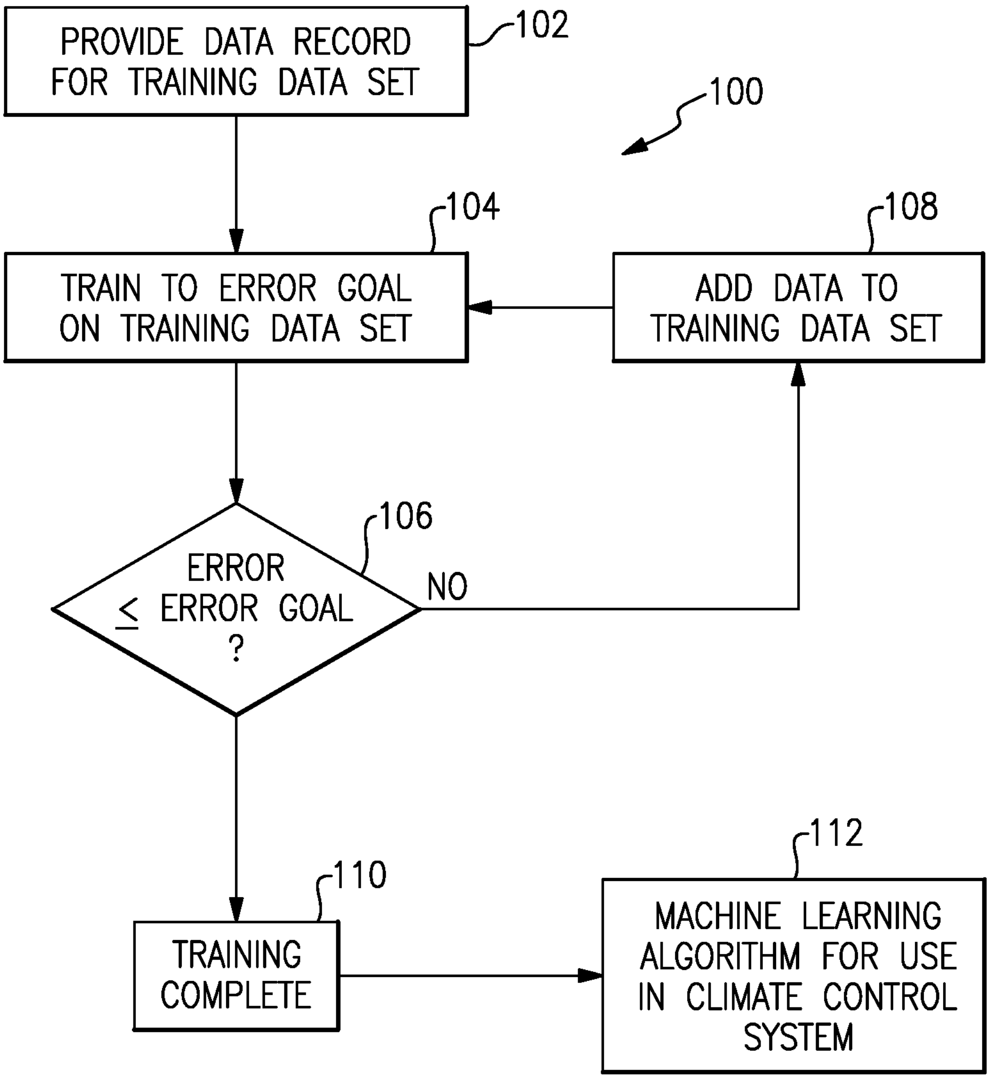
PROVIDE DATA RECORD FOR TRAINING DATA SET
102
100
104
108
TRAIN TO ERROR GOAL ON TRAINING DATA SET
ADD DATA TO TRAINING DATA SET
106
ERROR ≤ ERROR GOAL ?
NO
112
110
TRAINING COMPLETE
MACHINE LEARNING ALGORITHM FOR USE IN CLIMATE CONTROL SYSTEM

FIG.2

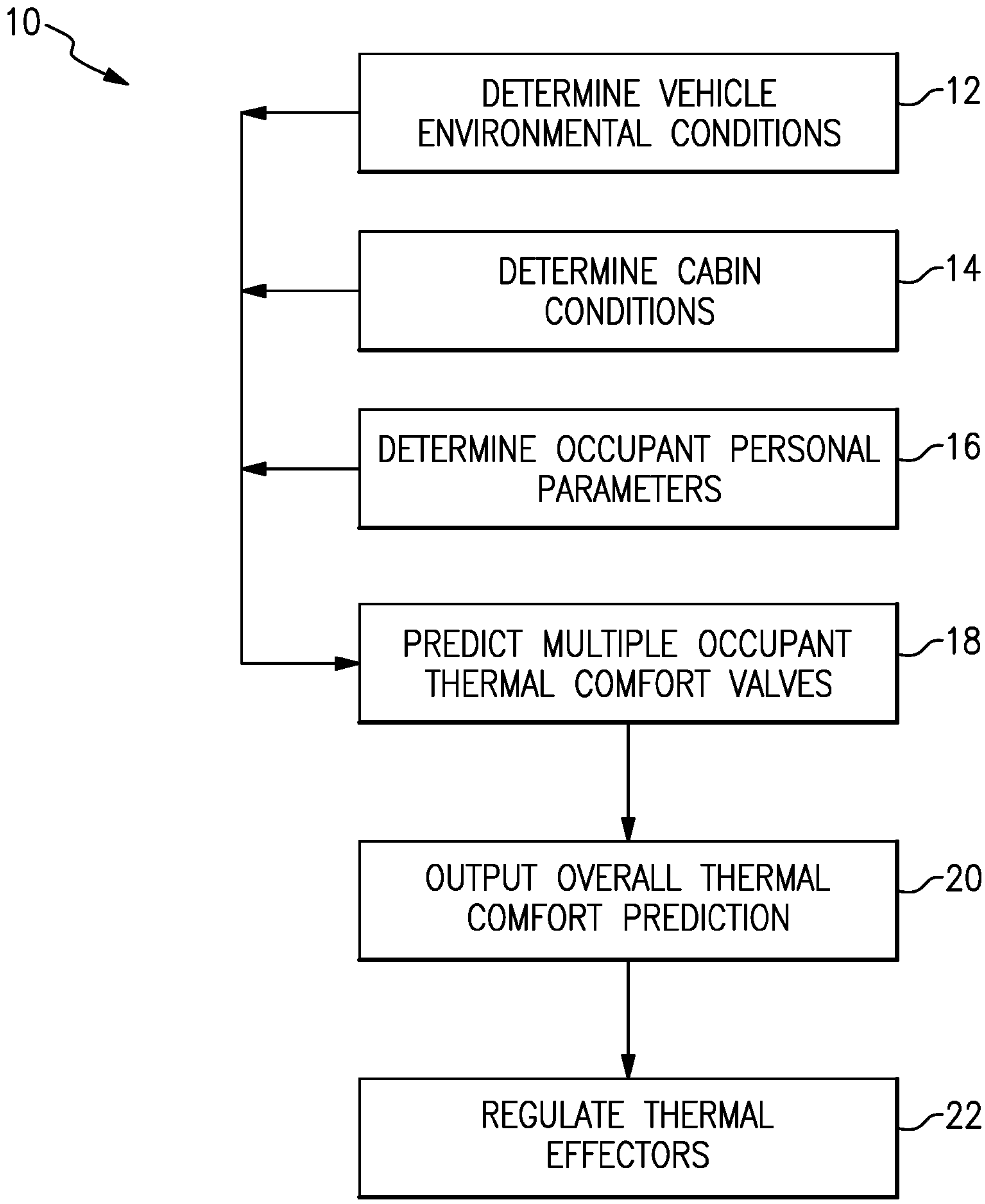
10
DETERMINE VEHICLE ENVIRONMENTAL CONDITIONS
12
DETERMINE CABIN CONDITIONS
14
DETERMINE OCCUPANT PERSONAL PARAMETERS
16
PREDICT MULTIPLE OCCUPANT THERMAL COMFORT VALVES
18
OUTPUT OVERALL THERMAL COMFORT PREDICTION
20
REGULATE THERMAL EFFECTORS
22

FIG.3

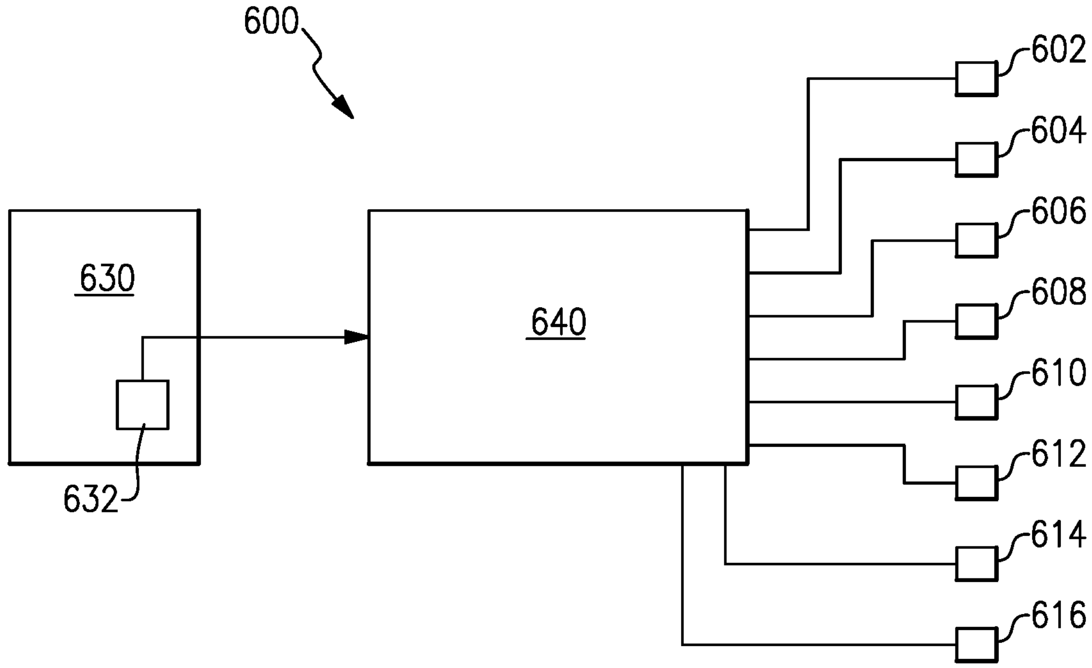

FIG.4

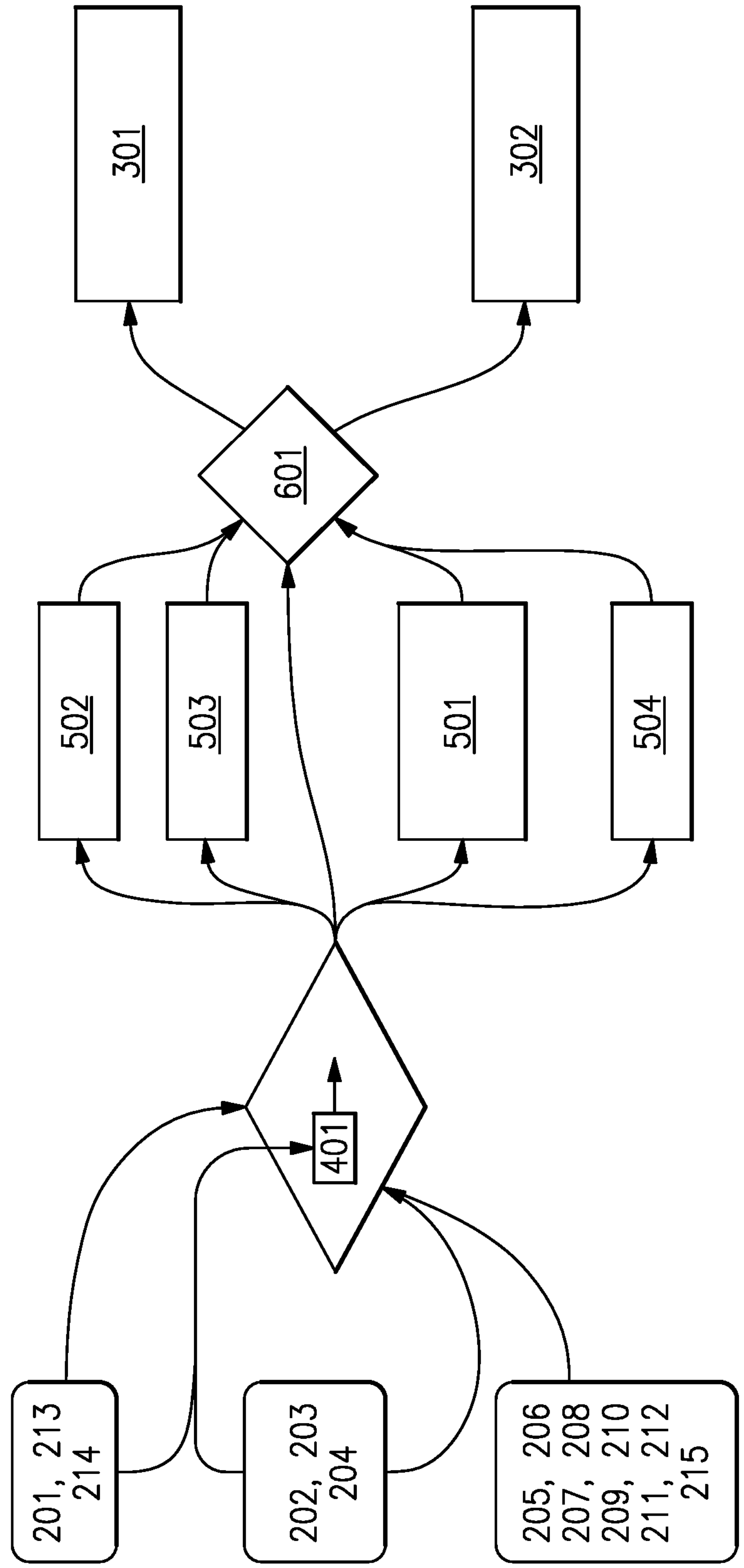
301
302
601
502
503
501
504
401
201, 213
214
202, 203
204
205, 206
207, 208
209, 210
211, 212
215

FIG.5

INTERNATIONAL SEARCH REPORT

International application No
PCT/US2021/042320

A. CLASSIFICATION OF SUBJECT MATTER
INV. B60H1/00 F24F11/62
ADD.

According to International Patent Classification (IPC) or to both national classification and IPC

B. FIELDS SEARCHED

Minimum documentation searched (classification system followed by classification symbols)
B60H F24F

Documentation searched other than minimum documentation to the extent that such documents are included in the fields searched

Electronic data base consulted during the international search (name of data base and, where practicable, search terms used)

EPO-Internal, WPI Data

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Category*	Citation of document, with indication, where appropriate, of the relevant passages	Relevant to claim No.
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Y	paragraphs [0184], [0221] - [0250]; claims 1-6; figures 7-17 -----	4,6,12, 14,18,23
Y	FR 3 086 582 A1 (VALEO SYSTEMES THERMIQUES [FR]) 3 April 2020 (2020-04-03) pages 10-13; claims 1-6,9; figures 1-3 -----	4,18
Y	US 2020/031195 A1 (WOODS MATTHEW [US] ET AL) 30 January 2020 (2020-01-30) paragraphs [0052] - [0056]; figure 2A -----	6,14,23
	-/--	

[X] Further documents are listed in the continuation of Box C.

[X] See patent family annex.

* Special categories of cited documents :

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"O" document referring to an oral disclosure, use, exhibition or other means

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"T" later document published after the international filing date or priority date and not in conflict with the application but cited to understand the principle or theory underlying the invention

"X" document of particular relevance; the claimed invention cannot be considered novel or cannot be considered to involve an inventive step when the document is taken alone

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"&" document member of the same patent family

Date of the actual completion of the international search	Date of mailing of the international search report
26 October 2021	05/11/2021

Name and mailing address of the ISA/	Authorized officer
European Patent Office, P.B. 5818 Patentlaan 2 NL - 2280 HV Rijswijk Tel. (+31-70) 340-2040, Fax: (+31-70) 340-3016	Kristensen, Julien

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C(Continuation). DOCUMENTS CONSIDERED TO BE RELEVANT

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1

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International application No
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