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(54) ESTIMATING WEAR OF A CUTTING ELEMENT

(57) The subject-matter of the present disclosure relates to a computer-implemented method of estimating cutting element wear of a personal care appliance. The computer-implemented method comprises: receiving (S200), from a sensor of the personal care appliance, physical parameters associated with operating the personal care appliance; estimating (S203), using a machine learning model, cutting element wear based on the sensed physical parameters; and sending (5204) a signal indicating the estimated cutting element wear.

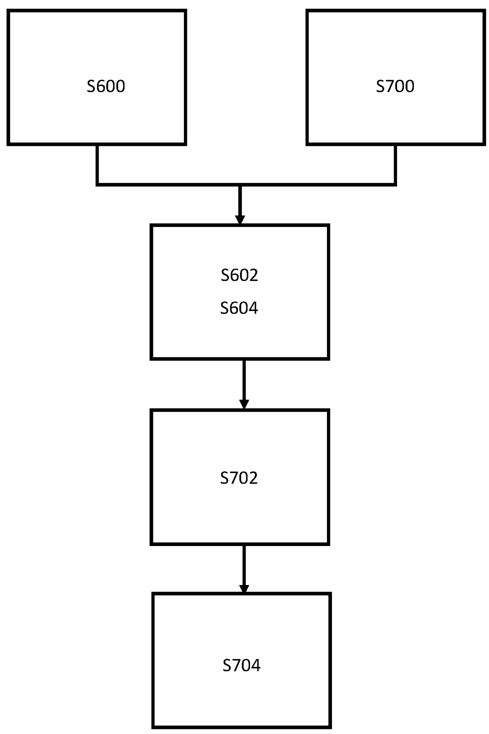

Figure 8

Processed by Luminess, 75001 PARIS (FR)

Description

FIELD OF THE INVENTION

[0001] The subject-matter of the present disclosure relates to estimating wear of a cutting element of a personal care appliance, estimating a degree of wear for a user of a personal care appliance, training a machine learning model to estimate wear of a cutting element of a personal care appliance, transitory, or non-transitory, computer-readable media, and personal care appliances including cutting elements.

BACKGROUND OF THE INVENTION

[0002] Currently, to understand cutting element wear, personal care appliances rely on either a pad print to show up or a prolonged period of shaves, e.g. 170 minutes. Both methods have their drawbacks, resulting in either not accommodating the individualistic characteristics of the beard of a particular user or not covering a number of ways in which the personal care appliance might be used. Therefore, they may be providing inaccurate information on the wear of the cutting element, thus leading to a suboptimal shaving experience.

[0003] It is an aim of the subject-matter of the present disclosure to improve on the prior art.

SUMMARY OF THE INVENTION

[0004] According to a first aspect of the present invention, there is provided a computer-implemented method of estimating wear of a cutting element of a personal care appliance, the computer-implemented method comprising: receiving, from a sensor of the personal care appliance, physical parameters associated with operating the personal care appliance; estimating, using a machine learning model, cutting element wear based on the sensed physical parameters; and sending a signal indicating the estimated cutting element wear. Estimating cutting element wear in this way provides a more personalised estimation which is based on the actual shaves of the user. For example, the user's bear length and sensitivity is taken into account. In this way, the users have a more consistent shaving experience and have knowledge of when to replace their cutting elements, thereby, reducing the risk of having to go through painful shaves in order to understand when a change of a cutting element is needed.

[0005] In an embodiment, the physical parameters include current and/or power of a motor used to drive the cutting element.

[0006] In an embodiment, the computer-implemented method further comprises calculating a plurality of predictors using the physical parameters, and wherein the estimating cutting element wear based on the sensed physical parameters comprises inputting, to the machine learning model, the plurality of predictors.

[0007] In an embodiment, the plurality of predictors are selected from a list of predictors including: a binned distribution of motor power of a last use, an average motor current of last use, a binned distribution of motor power of a last use minus one, a maximum power of the last use minus one, an average motor current of the last use minus one, a binned distribution of motor power of a last use minus two, an absolute maximum current of a last use minus two, a maximum power of a last use minus two, an average motor current of last use minus two, a binned distribution of a difference between motor power between a last use and a first three uses, a binned distribution of motor power averaged over first three uses, an average absolute maximum current of the last three uses, a maximum power ratio between last use and an average from the first three uses, a maximum power from amongst the last three uses, an average maximum power of the last three uses, a difference between a last use and the previous use's average motor current, a different of last use's average motor current and average motor current averaged over first three uses, a ratio of last use's average motor current and average motor current averaged over first three uses, and an average motor current averaged over first three uses.

[0008] A use may be a shave in some embodiments. The binned distribution may be visualised as a histogram.

[0009] In an embodiment, the machine learning model is a random forest regressor trained to output a numerical value denoting an estimate of cutting element wear.

[0010] In an embodiment, the random forest regressor include three estimators, has a maximum depth of 12, and has a minimum samples leaf of 2.

[0011] According to an aspect of the present invention, there is provided a computer-implemented method of estimating a degree of wear of a cutting element for a user of a personal care appliance, the computer-implemented method comprising: estimating cutting element wear using the computer-implemented method of any preceding claim, wherein the machine learning model is a first machine learning model; classifying sensitivity of the user by: receiving, from the sensor, data representing physical parameters associated with operating the personal care appliance, and assigning, using a second machine learning model, a user to a classification of sensitivity to the cutting element of the personal care appliance based on the received data; determining a maximum cutting element wear value of a user based on their classification; calculating a degree of cutting element wear based on the determined maximum cutting element wear value and the estimated cutting element wear; and sending a signal indicating the calculated degree of cutting element wear.

[0012] In this way, the degree of cutting element wear is personalised to the user and their pattern of shaving.

[0013] In an embodiment, the calculating the degree of cutting element wear comprises using:

$$D = \left(1 - \frac{cRPS}{EoL\ RPS}\right) x100 \ ,$$

where D is the degree or cutting element wear, cRPS denotes the estimated cutting element wear, and EoL RPS denotes the maximum cutting element wear of a user.

[0014] According to an aspect of the present invention, there is provided a computer-implemented method of training a machine learning model to estimate wear of a cutting element of a personal care appliance, the computer-implemented method comprising: receiving a data set including a plurality of predictors derived from physical parameters sensed by a sensor of the personal care appliance, and values corresponding to estimates of cutting element wear, the physical parameters associated with operation of the personal care appliance; constructing the machine learning model using at least some data from the data set; and optimising the machine learning model to improve accuracy in predicting the values corresponding to estimates of cutting element wear.

[0015] In an embodiment, the machine learning model is a random forest regressor, wherein the constructing the machine learning model using at least some data from the data set comprises: iteratively excluding data associated with one personal care appliance from amongst a plurality of personal care appliances upon which the data set is based; and constructing the random forest regressor by bootstrapping non-excluded data from the data set.

[0016] In an embodiment, the optimising the machine learning model comprises: applying k-fold cross-validation using the excluded data.

[0017] In an embodiment, the data set including predictors in columns, and estimated cutting element wear values in rows.

[0018] In an embodiment, the physical parameters include current and/or power of a motor used to drive the cutting element. Using such parameters is useful since each user would have a different gradient of increase of motor current, and thereby, the cutting element wear esimtate, each of them would have different rate of wear, making it more personal than the existing solutions.

[0019] In an embodiment, the plurality of predictors are selected from a list of predictors including: a binned distribution of motor power of a last use, an average motor current of last use, a binned distribution of motor power of a last use minus one, a maximum power of the last use minus one, an average motor current of the last use minus one, a binned distribution of motor power of a last use minus two, an absolute maximum current of a last use minus two, a maximum power of a last use minus two, an average motor current of last use minus two, a binned distribution of a difference between motor power between a last use and a first three uses, a binned distribution of motor power averaged over first three uses, an average absolute maximum current of the last three uses, a maximum power ratio between last use and an average from the first three uses, a maximum power from amongst the last three uses, an average maximum power of the last three uses, a difference between a last use and the previous use's average motor current, a different of last use's average motor current and average motor current averaged over first three uses, a ratio of last use's average motor current and average motor current averaged over first three uses, and an average motor current averaged over first three uses.

[0020] According to an aspect of the present invention, there is provided a transitory, or non-transitory, computer-readable medium, having instructions stored thereon that, when executed by a processor, cause the processor to perform the computer-implemented method of any preceding aspect or embodiment.

[0021] According to an aspect of the present disclosure, there is provided a personal care appliance, comprising: an attachment for attaching to a cutting element; a sensor for sensing physical parameters associated with operating the personal care appliance; and a controller having a processor and storage, the storage having instructions stored thereon that, when executed by the processor, cause the processor to perform the computer-implemented method of any preceding aspect or embodiment.

[0022] These and other aspects of the present invention will be apparent from and elucidated with reference to the embodiment(s) described hereinafter.

BRIEF DESCRIPTION OF THE DRAWINGS

[0023] The embodiments of the present inventions may be best understood with reference to the accompanying figures, in which:

Fig. 1 shows a schematic view of a personal care appliance according to one or more embodiments;
Fig. 2 shows a flow chart summarising a computer-implemented method of estimating wear of a cutting element of the personal care appliance from Fig. 1, according to one or more embodiments;
Fig. 3 shows a flow chart summarising a computer-implemented method of training a machine learning model to estimate wear of a cutting element of the personal care appliance from Fig. 1, according to one or more embodiments;
Fig. 4 shows a flow chart summarising the computer-implemented method of Fig. 3 in a different way, according to one or more embodiments;
Fig. 5 shows a flow chart summarising a computer-implemented method of classifying sensitivity of a user to a treatment head of an appliance, according to one or more embodiments;
Fig. 6 shows a decision tree, according to one or more embodiments;
Fig. 7 shows a flow chart summarising a computer-implemented method of training the machine learn-

ing model from Fig. 5, according to one or more embodiments;

Fig. 8 shows a flow chart summarising in a different way the computer-implemented method of training the machine learning model from Fig. 5, according to one or more embodiments; and

Fig. 9 shows a flow chart summarising a computer-implemented method of calculating a degree of treatment hear wear of an appliance according to one or more embodiments.

DETAILED DESCRIPTION OF THE EMBODIMENTS

[0024] At least some of the example embodiments described herein may be constructed, partially or wholly, using dedicated special-purpose hardware. Terms such as 'component', 'module' or 'unit' used herein may include, but are not limited to, a hardware device, such as circuitry in the form of discrete or integrated components, a Field Programmable Gate Array (FPGA) or Application Specific Integrated Circuit (ASIC), which performs certain tasks or provides the associated functionality. In some embodiments, the described elements may be configured to reside on a tangible, persistent, addressable storage medium and may be configured to execute on one or more processors. These functional elements may in some embodiments include, by way of example, components, such as software components, object-oriented software components, class components and task components, processes, functions, attributes, procedures, subroutines, segments of program code, drivers, firmware, microcode, circuitry, data, databases, data structures, tables, arrays, and variables. Although the example embodiments have been described with reference to the components, modules and units discussed herein, such functional elements may be combined into fewer elements or separated into additional elements. Various combinations of optional features have been described herein, and it will be appreciated that described features may be combined in any suitable combination. In particular, the features of any one example embodiment may be combined with features of any other embodiment, as appropriate, except where such combinations are mutually exclusive. Throughout this specification, the term "comprising" or "comprises" means including the component(s) specified but not to the exclusion of the presence of others.

[0025] With reference to Fig. 1, a personal care appliance 10 including a cutting element 12 and a handle 14. The personal care appliance 10 may be a grooming appliance such as a hair cutting appliance. Hair cutting appliances generally involve hair trimmers, shavers, epilators, and combined devices. The personal care appliance 10 may be used for trimming and shaving.

[0026] The cutting element 12 comprises a stator and a moveable blade each comprising teeth. The moveable blade moves relative to the stator to cut hair between the teeth.

[0027] The handle 14 is elongate and has an attachment 15 for attaching to the cutting element. In other words, the attachment 15 is for attaching the cutting element 12 to the handle. The personal care appliance 10 further comprises a motor 16, a sensor 18, a controller 20, and an energy storage unit 22.

[0028] The motor 16 may be an electric motor 16 and may be connected to the cutting element to drive the blade. The motor 16 is powered by energy from the storage unit 22. The sensor may be a sensor 18 is configured to sense physical parameters associated with operating the personal care appliance. The physical parameters include current and/or power of the motor 16.

[0029] The controller 20 comprises a processor 24 and storage 26. The storage 26 has instructions stored thereon that, when executed by the processor 24, cause the processor to perform any of the methods described below. The storage may thus form non-transitory, computer-readable media having instructions stored thereon that when executed by the processor cause the processor to perform any of the methods described herein. The instructions may also be provided on transitory computer-readable media that can be added to the storage when, for example, an update is required.

[0030] With reference to Fig. 2, a computer-implemented method of estimating wear of the cutting element of the personal care appliance is summarised as having steps including: receiving S200, from a sensor of the personal care appliance, physical parameters associated with operating the personal care appliance; estimating S202, using a machine learning model, cutting element wear based on the sensed physical parameters; and sending S204 a signal indicating the estimated cutting element wear. The machine learning model may be a first machine learning model.

[0031] In other words, during inference, the machine learning model is used to estimate wear of the cutting element based on the sensor data, e.g. motor current, power, etc., of a new use, or shave. The blade wear estimation output by the machine learning model may be a numerical value. The numerical value may be called a robot pulling score (RPS). The robot pulling score obtained during a current shave is called a current robot pulling score cRPS, which is an objective representation of the state of the cutting element or an estimation of wear of the cutting element.

[0032] In this way, the machine learning model may be a random forest regressor trained to output the numerical value denoting an estimate of cutting element wear. In order to obtain the numerical value from the random forest regressor, first a plurality of predictors are calculated using the physical parameters (e.g. motor current and/or power). The plurality of predictors are then input to the machine learning model.

[0033] The plurality of predictors may be selected from a list of predictors including: a binned distribution of motor power of a last use, an average motor current of last use, a binned distribution of motor power of a last use minus one, a maximum power of the last use minus one, an average motor current of the last use minus one, a binned distribution of motor power of a last use minus two, an absolute maximum current of a last use minus two, a maximum power of a last use minus two, an average motor current of last use minus two, a binned distribution of a difference between motor power between a last use and a first three uses, a binned distribution of motor power averaged over first three uses, an average absolute maximum current of the last three uses, a maximum power ratio between last use and an average from the first three uses, a maximum power from amongst the last three uses, an average maximum power of the last three uses, a difference between a last use and the previous use's average motor current, a different of last use's average motor current and average motor current averaged over first three uses, a ratio of last use's average motor current and average motor current averaged over first three uses, and an average motor current averaged over first three uses.

[0034] The random forest regressor may include three estimators, have a maximum depth of 12, and have a minimum samples lead of 2.

[0035] With reference to Fig. 3, a computer-implemented method of training the machine learning model to estimate wear of a cutting element of a personal care appliance is summarised as having steps including: receiving S300 a data set including a plurality of predictors derived from physical parameters sensed by a sensor of the personal care appliance, and values corresponding to estimates of cutting element wear, the physical parameters associated with operation of the personal care appliance; constructing S302 the machine learning model using at least some data from the data set; and optimising S304 the machine learning model to improve accuracy in predicting the values corresponding to estimates of cutting element wear.

[0036] With reference to Fig. 4, step S300 may be divided into S300A and S300B. Step S300A may be collecting sensor data associated with physical parameters, and then computing the plurality of predictors. The predictors may be the same as described above for the machine learning model during inference. Step S300B may be collecting lab test results including RPS values. The RPS values will be associated with the sensor data since an RPS value for each use of the personal care appliance can be obtained and associated with the sensor data for that use. In addition, the users may fill in a questionnaire scoring various aspects of the shave.

[0037] Steps S302 and S304 of Fig. 3 may be equated in a single block in Fig. 4. The constructing the machine learning model may include iteratively excluding data associated with one personal care appliance from amongst a plurality of personal care appliances based, and constructing the random forest regressor by bootstrapping non-excluded data from the data set. The optimising the machine learning model may comprise applying k-fold cross-validation using the excluded data.

[0038] It should be noted that when pre-processing the data for training the machine learning model, the data set is processed to include the predictors in columns and the estimated wear values of the cutting element (RPS values) in rows.

[0039] Step S306 of Fig. 4 corresponds to step S204 of Fig. 2, namely sending a signal indicating the estimated cutting element wear. This signal may include the RPS value. Using the RPS value, further inference can be obtained to classify a user according to a particular rate of wear. There may be three rate of wear segments that a user can be classified in. Those three segments may include: segment 1, slow wear (e.g. when there is a difference of 0.03 in RPS value between uses); segment 2, steady wear (e.g. when there is a difference between 0.03 and 0.05 in RPS value between uses); and segment 3, fast wear (e.g. when there is a difference between 0.05 in RPS value between uses).

[0040] With reference to Fig. 5, according to one or more further embodiments, a computer-implemented method of classifying sensitivity of a user to a treatment head of an appliance may be summarised to have steps including: receiving S500, from a sensor of the appliance, data representing physical parameters associated with operating the appliance; assigning S502, using a machine learning model, a user to a classification of sensitivity to a treatment head of the appliance based on the received data; and sending S504 a signal indicating the assigned classification.

[0041] The appliance may be a personal care appliance, such as the personal care appliance of Fig. 1. The treatment head may be the cutting element. The machine learning model of this embodiment may be a second machine learning model.

[0042] The physical parameters in this embodiment may include current and/or power of the motor used to drive the treatment head.

[0043] In this embodiment, the machine learning model may be a decision tree.

[0044] The assigning the user to the classification may comprise calculating a plurality of predictors using the data representing the physical parameters, inputting the plurality of predictors to inputs of the decision tree and outputting from the decision tree the classification of the user to the sensitivity to the treatment head of the appliance. The predictors in this embodiment may be selected from a different list of descriptors than previous embodiments. The list of descriptors for this embodiment may include a binned distribution of motor power values from first three uses, a binned distribution of motor power of a first use, a binned distribution of motor power values of each use from amongst first to third uses, and a binned distribution of power values of a last use.

[0045] A first class may be used for non-sensitive users, a second class may be used for normal-sensitive users, and a third class may be used for sensitive users. The terms first to third do not denote any particular order of classification but are used to distinguished between the classes.

[0046] With reference to Fig. 6, the decision tree 30 includes a plurality of nodes 32. Each node 32 is either a branch node or a leaf node. The branch node provides a split leading to two new nodes. The leaf nodes are output nodes outputting a classifying sensitivity of a user to a treatment head of an appliance. The splits are different for each level of the tree, and each branch of the tree. The splits may be numerical values and may be decided by training the machine learning model as explained below. One of the predictors 38 is applied after each branch node. The predictor 38 applied at each branch may be different. All of the foregoing predictors may be used at some point of the decision tree 30. The value of the predictor is compared to the split and if the predictor is less than or equal to the split, a first branch is taken. If the predictor is greater than the split, a second branch is taken. In Fig. 6, the first branch is a left branch, and the second branch is a right branch. This convention may be altered in other embodiments.

[0047] The three classes output at the leaf nodes may be a first class 34 may be used for non-sensitive users, a second class 35 may be used for normal-sensitive users, and a third class 36 may be used for sensitive users. The terms first to third do not denote any particular order of classification, but are used to distinguished between the classes.

[0048] With reference to Fig. 7, a computer-implemented method of training the machine learning model (i.e. the second machine learning model) to assign a user to a classification of sensitivity to a treatment head of an appliance may be summarised as having steps including: receiving S600 a data set including a plurality of classifications, and a plurality of predictors derived from data sensed from a sensor of the appliance, the data representing physical parameters associated with operating the appliance; inputting S602 the plurality of predictors to the machine learning model to assign the user to a classification according to one of the plurality of classifications; and optimising S604 the machine learning model to reduce error between the assigned classification and the classification in the data set.

[0049] Again, the classifications include a first class for non-sensitive users, a second class for normal sensitive users, and a third class for sensitive users. The machine learning model may be the machine learning model outlined above with reference to Fig. 5, namely the second machine learning model. The predictors may be the same as those outlined above with reference to Fig. 5. The physical parameters may include current and/or power of a motor used to drive the treatment head.

[0050] The optimising the machine learning model may be performed using a classification and regression tree algorithm, CART algorithm. The CART algorithm may generate the splits identified above in relation to second machine learning model referenced when discussing Fig. 5.

[0051] The plurality of classifications may be generated by receiving scores from a user for each aspect of using the appliance, and calculating thresholds for each classification based on differences between subsegments of users. The aspects may include overall performance, comfort during a use, pulling hairs during a use, a burning feeling during a use, and redness during the use. These aspects may be input manually by a user to a user interface device (not shown) in response to a questionnaire during the lab tests when obtaining the training data set.

[0052] Fig. 8 shows a different way of summarising the embodiment of Figs. 5 and 6.

[0053] With reference to Fig. 8, step S600 may be input to the second machine learning model in addition to Step 700. Step 700 includes responses to a questionnaire to gather user data and feedback for each user. The feedback may include the aspects described above. The questionnaire may be populated after each shave during a training period, optionally in a lab setting.

[0054] Steps S602 and S604 are combined in one block in Fig. 8. Step S702 may correspond to obtaining the class of the user (e.g. first to third class). Step S704 may involve adjusting an end of life blade wear value based on the class of the user. The end-of-life blade wear value may be a RPS value (EoL RPS or end-of-life robot pulling score value) as in the above embodiments and may be predetermined. The EoL RPS may be a maximum treatment head wear value of a user based on their classification. In other words, there may be a predetermined maximum blade wear value, which is adjusted based on the user's sensitivity class. On reaching the end-of-life blade wear value, a signal is sent to a display device to signal to the user that the blade, or treatment head, needs to be replaced.

[0055] With reference to Fig. 9, the foregoing embodiments may be combined in holistic method of calculating a degree of treatment head wear of an appliance. The method may be a computer-implemented method and may include the following steps: receiving S200, from a sensor of the personal care appliance, physical parameters associated with operating the personal care appliance; estimating S202, using a machine learning model, cutting element wear based on the sensed physical parameters; and sending S204 a signal indicating the estimated cutting element wear. The method also comprises the steps of receiving questionnaire data S800 from a user interface device 802, to train the second machine learning mode. The method may also comprise assigning S502, using the second machine learning model, a user to a classification of sensitivity to a treatment head (e.g. a cutting element), of the appliance (e.g. personal care appliance), based on the received sensor data. The method may also comprise calculating S704, and sending, the maximum treatment head (e.g. cutting element) wear value, EoL RPS, of a user based on their classification.

[0056] The method also comprises calculating S804 a degree of treatment head (e.g. cutting element) wear based on the determined maximum treatment head (e.g. cutting element) wear value and the estimated treatment head (e.g. cutting element) wear. The method also comprises sending S806 a signal indicating the calculated degree of treatment head wear to a user interface device 802 or a display of the appliance 10.

[0057] In some embodiments, the calculating the degree of treatment head wear comprises using:

$$D = \left(1 - \frac{cRPS}{EoL\ RPS}\right) x100,$$

where D is the degree or treatment head wear, cRPS denotes the estimated treatment head wear, and EoL RPS denotes the maximum treatment head wear of a user.

[0058] While the invention has been illustrated and described in detail in the drawings and foregoing description, such illustration and description are to be considered illustrative or exemplary and not restrictive; the invention is not limited to the disclosed embodiments.

[0059] Other variations to the disclosed embodiments can be understood and effected by those skilled in the art in practicing the claimed invention, from a study of the drawings, the disclosure, and the appended claims. In the claims, the word "comprising" does not exclude other elements or steps, and the indefinite article "a" or "an" does not exclude a plurality. A single processor or other unit may fulfil the functions of several items recited in the claims. The mere fact that certain measures are recited in mutually different dependent claims does not indicate that a combination of these measured cannot be used to advantage. Any reference signs in the claims should not be construed as limiting the scope.

[0060] The following clauses may be used to understand various aspects of the present disclosure.

[0061] Clause 1. A computer-implemented method of classifying sensitivity of a user to a treatment head of a appliance, the computer-implemented method comprising: receiving, from a sensor of the appliance, data representing physical parameters associated with operating the appliance; assigning, using a machine learning model, a user to a classification of sensitivity to a treatment head of the appliance based on the received data; and sending a signal indicating the assigned classification.

[0062] Clause 2. The computer-implemented method of Clause 1, wherein the physical parameters include current and/or power of a motor used to drive the treatment head.

[0063] Clause 3. The computer-implemented method of Clause 1 or Clause 2, wherein the machine learning model is a decision tree.

[0064] Clause 4. The computer-implemented method of Clause 3, wherein the assigning, using a machine learning model, the user to the classification of sensitivity to the treatment head of the appliance based on the received data comprises: calculating a plurality of predictors using the data representing the physical parameters; inputting the plurality of predictors to inputs of the decision tree; and outputting, from the decision tree, the classification of the user to the sensitivity to the treatment head of the appliance.

[0065] Clause 5. The computer-implemented method of Clause 4, wherein the plurality of predictors is selected from a list of predictors including: a binned distribution of motor power values from first three uses, a binned distribution of motor power of a first use, a binned distribution of motor power values of each use from amongst first to third uses, and a binned distribution of power values of a last use.

[0066] Clause 6. The computer-implemented method of Clause 5, wherein a first class is used for non-sensitive users, a second class is used for normal-sensitive users, and a third class is used for sensitive users.

[0067] Clause 7. A computer-implemented method of calculating a degree of treatment head wear of a appliance, comprising: assigning a user to a classification of sensitivity using the method of any preceding clause, wherein the machine learning model is a second machine learning model; determining a maximum treatment head wear value of a user based on their classification; estimating a treatment head wear by: receiving, from the sensor, physical parameters associated with operating the appliance, estimating, using a first machine learning model, treatment head wear based on the sensed physical parameters; calculating the degree of treatment head wear based on the determined maximum treatment head wear value and the estimated treatment head wear; and sending a signal indicating the calculated degree of treatment head wear.

[0068] Clause 8. The computer-implemented method of Clause 7, wherein the calculating the degree of treatment head wear comprises using: $D = \left(1 - \frac{cRPS}{EoL\ RPS}\right) x100$, where D is the degree or treatment head wear, cRPS denotes the estimated treatment head wear, and EoL RPS denotes the maximum treatment head wear of a user.

[0069] Clause 9. A computer-implemented method of training a machine learning model to assign a user to a classification of sensitivity to a treatment head of an appliance, the computer-implemented method comprising: receiving a data set including a plurality of classifications, and a plurality of predictors derived from data sensed from a sensor of the appliance, the data representing physical parameters associated with operating the appliance; inputting the plurality of predictors to the machine learning model to assign the user to a classification according to one of the plurality of classifications; and optimising the machine learning model to reduce error between the assigned classification and the classification in the data set.

[0070] Clause 10. The computer-implemented method of Clause 9, wherein the classifications including a first class for non-sensitive users, a second class for normal sensitive users, and a third class for sensitive users.

[0071] Clause 11. The computer-implemented method of Clause 9 or Clause 10, wherein the machine learning model is a decision tree.

[0072] Clause 12. The computer-implemented method of Clause 11, wherein the optimising the machine learning model is performed using a classification and regression tree algorithm.

[0073] Clause 13. The computer-implemented method of any of Clauses 9 to 12, wherein the physical parameters includes current and/or power of a motor used to drive the treatment head.

[0074] Clause 14. The computer-implemented method of Clause 13, wherein the plurality of predictors is selected from a list of predictors including: a binned distribution of motor power values from first three uses, a binned distribution of motor power of a first use, a binned distribution of motor power values of each use from amongst first to third uses, and a binned distribution of power values of a last use.

[0075] Clause 15. The computer-implemented method of any of Clauses 9 to 14, comprising generating the plurality of classifications by receiving scores from a user for each aspect of using the appliance, and calculating thresholds for each classification based on differences between subsegments of users, wherein optionally the aspects include overall performance, comfort during a use, pulling hairs during a use, a burning feeling during a use, and redness during the use.

[0076] Clause 16. The computer-implemented method of any preceding claim, wherein the appliance is a personal care appliance and optionally wherein the treatment head is a cutting element.

[0077] Clause 17. A transitory, or non-transitory, computer-readable medium having instructions stored thereon that, when executed by a processor, cause the processor to perform the computer-implemented method of any preceding clause.

[0078] Clause 18. An appliance, including: an attachment for attaching a treatment head thereto; a sensor for sensing physical parameters associated with operating the appliance; and a controller including a processor and storage, the storage having instructions stored thereon that when executed by the processor cause the processor to perform the computer- implemented method of any of Clauses 1 to 8.

Claims

1. A computer-implemented method of estimating wear of a cutting element (12) of a personal care appliance (10), the computer-implemented method comprising:

    receiving (S200), from a sensor of the personal care appliance, physical parameters associated with operating the personal care appliance;
    estimating (S202), using a machine learning model, cutting element wear based on the sensed physical parameters; and
    sending (S204) a signal indicating the estimated cutting element wear.

2. The computer-implemented method of Claim 1, wherein the physical parameters include current and/or power of a motor (16) used to drive the cutting element.

3. The computer-implemented method of Claim 2, further comprising calculating a plurality of predictors using the physical parameters, and wherein the estimating cutting element wear based on the sensed physical parameters comprises inputting, to the machine learning model, the plurality of predictors.

4. The computer-implemented method of Claim 3, wherein the plurality of predictors are selected from a list of predictors including:
    a binned distribution of motor power of a last use, an average motor current of last use, a binned distribution of motor power of a last use minus one, a maximum power of the last use minus one, an average motor current of the last use minus one, a binned distribution of motor power of a last use minus two, an absolute maximum current of a last use minus two, a maximum power of a last use minus two, an average motor current of last use minus two, a binned distribution of a difference between motor power between a last use and a first three uses, a binned distribution of motor power averaged over first three uses, an average absolute maximum current of the last three uses, a maximum power ratio between last use and an average from the first three uses, a maximum power from amongst the last three uses, an average maximum power of the last three uses, a difference between a last use and the previous use's average motor current, a different of last use's average motor current and average motor current averaged over first three uses, a ratio of last use's average motor current and average motor current averaged over first three uses, and an average motor current averaged over first three uses.

5. The computer-implemented method of any preceding claim, wherein the machine learning model is a random forest regressor trained to output a numerical value denoting an estimate of cutting element wear.

6. The computer-implemented method of Claim 5, wherein the random forest regressor include three estimators, has a maximum depth of 12, and has a minimum samples leaf of 2.

7. A computer-implemented method of estimating a degree of cutting element wear for a user of a personal care appliance, the computer-implemented method comprising:

estimating cutting element wear using the computer-implemented method of any preceding claim, wherein the machine learning model is a first machine learning model;
classifying sensitivity of the user by:

receiving (S500), from the sensor, data representing physical parameters associated with operating the personal care appliance, and
assigning (S502), using a second machine learning model, a user to a classification of sensitivity to the cutting element of the personal care appliance based on the received data;

determining (S704) a maximum cutting element wear value of a user based on their classification;
calculating (S804) a degree of cutting element wear based on the determined maximum cutting element wear value and the estimated cutting element wear; and
sending (S806) a signal indicating the calculated degree of cutting element wear.

8. The computer-implemented method of Claim 7, wherein the calculating the degree of cutting element wear comprises using:

$$D = \left(1 - \frac{cRPS}{EoL\ RPS}\right) x100 \ ,$$

where D is the degree or cutting element wear, cRPS denotes the estimated cutting element wear, and EoL RPS denotes the maximum cutting element wear of a user.

9. A computer-implemented method of training a machine learning model to estimate cutting element wear of a personal care appliance, the computer-implemented method comprising:

receiving (S300) a data set including a plurality of predictors derived from physical parameters sensed by a sensor of the personal care appliance, and values corresponding to estimates of cutting element wear, the physical parameters associated with operation of the personal care appliance;
constructing (S302) the machine learning model using at least some data from the data set; and
optimising (S304) the machine learning model to improve accuracy in predicting the values corresponding to estimates of cutting element wear.

10. The computer-implemented method of Claim 9, wherein the machine learning model is a random forest regressor, wherein the constructing the machine learning model using at least some data from the data set comprises:

iteratively excluding data associated with one personal care appliance from amongst a plurality of personal care appliances upon which the data set is based; and
constructing the random forest regressor by bootstrapping non-excluded data from the data set.

11. The computer-implemented method of Claim 10, wherein the optimising the machine learning model comprises:
applying k-fold cross-validation using the excluded data.

12. The computer-implemented method of any of Claims 9 to 11, wherein the data set including predictors in columns, and estimated cutting element wear values in rows.

13. The computer-implemented method of any of Claims 9 to 12, wherein the physical parameters include current and/or power of a motor used to drive the cutting element.

14. The computer-implemented method of any of Claims 9 to 13, wherein the plurality of predictors are selected from a list of predictors including:
a binned distribution of motor power of a last use, an average motor current of last use, a binned distribution of motor power of a last use minus one, a maximum power of the last use minus one, an average motor current of the last use minus one, a binned distribution of motor power of a last use minus two, an absolute maximum current of a last use minus two, a maximum power of a last use minus two, an average motor current of last use minus two, a binned distribution of a difference between motor power between a last use and a first three uses, a binned distribution of motor power averaged over first three uses, an average absolute maximum current of the last three uses, a maximum power ratio between last use and an average from the first three uses, a maximum power from amongst the last three uses, an average maximum power of the last three uses, a difference between a last use and the previous use's average motor current, a different of last use's average motor current and average motor

current averaged over first three uses, a ratio of last use's average motor current and average motor current averaged over first three uses, and an average motor current averaged over first three uses.

15. A personal care appliance (10), comprising:

an attachment for attaching to a cutting element (12);
a sensor (18) for sensing physical parameters associated with operating the personal care appliance; and
a controller (20) having a processor (22) and storage (24), the storage having instructions stored thereon that, when executed by the processor, cause the processor to perform the computer-implemented method of any preceding claim.

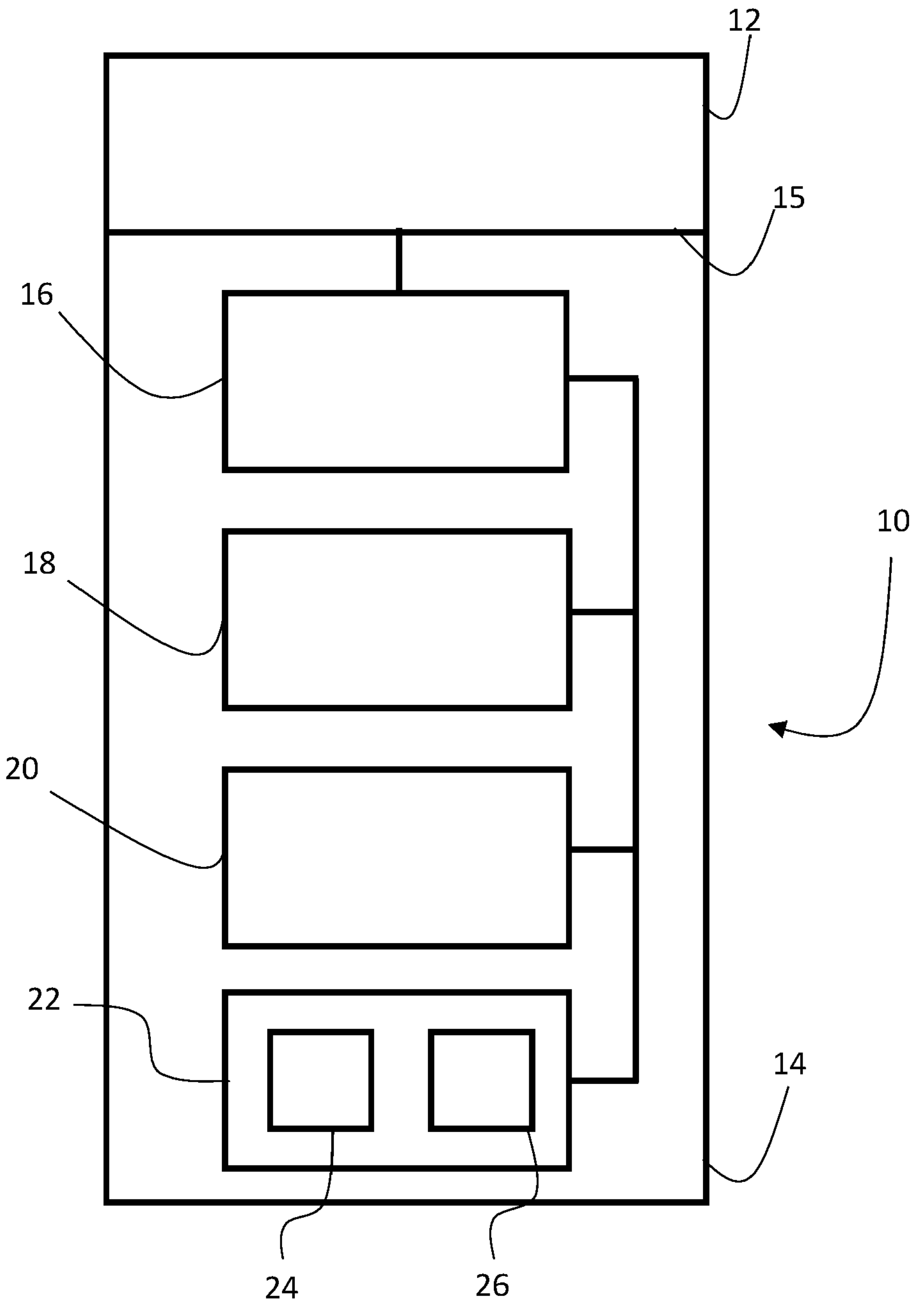

Figure 1

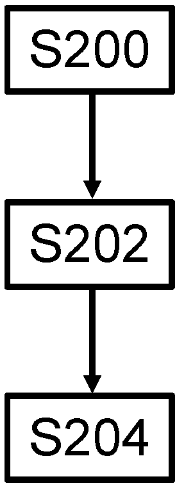

Figure 2

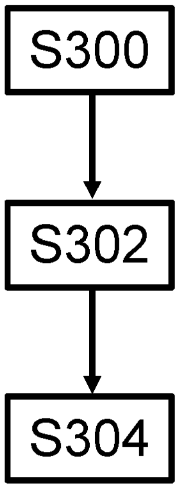

Figure 3

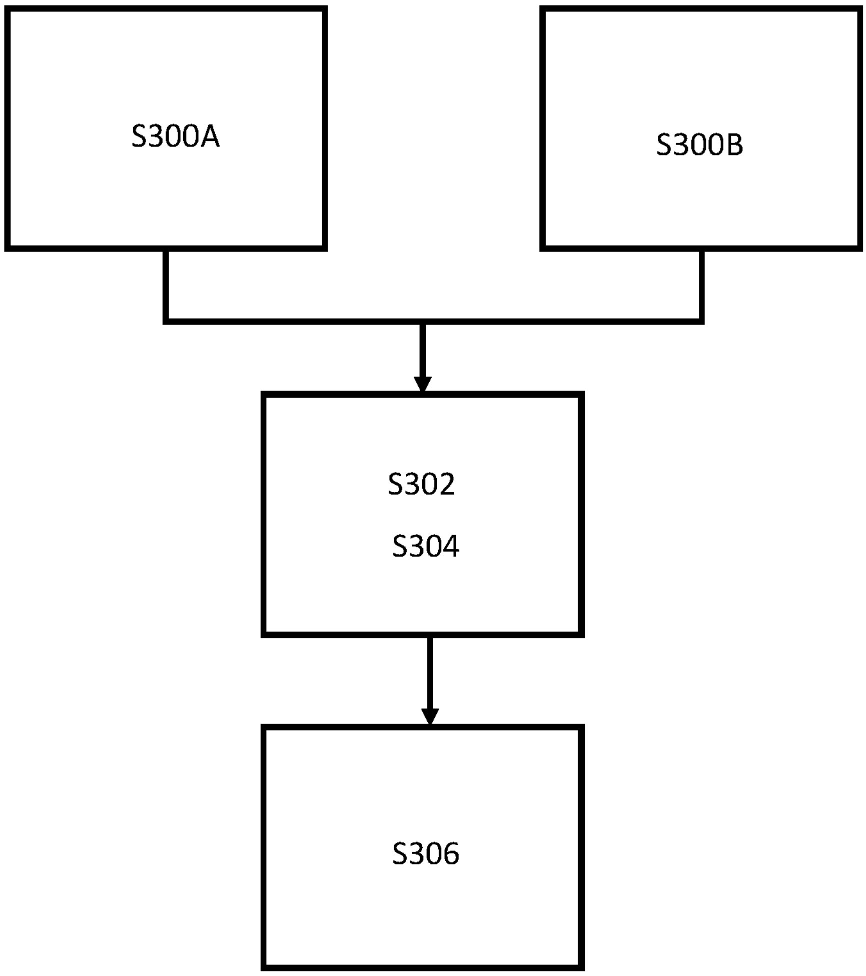

Figure 4

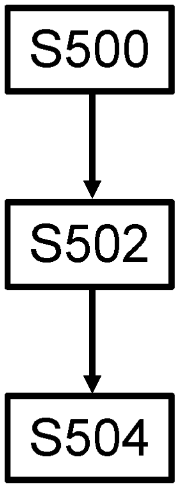

Figure 5

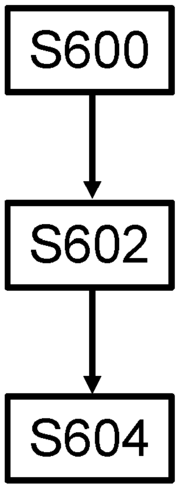

Figure 7

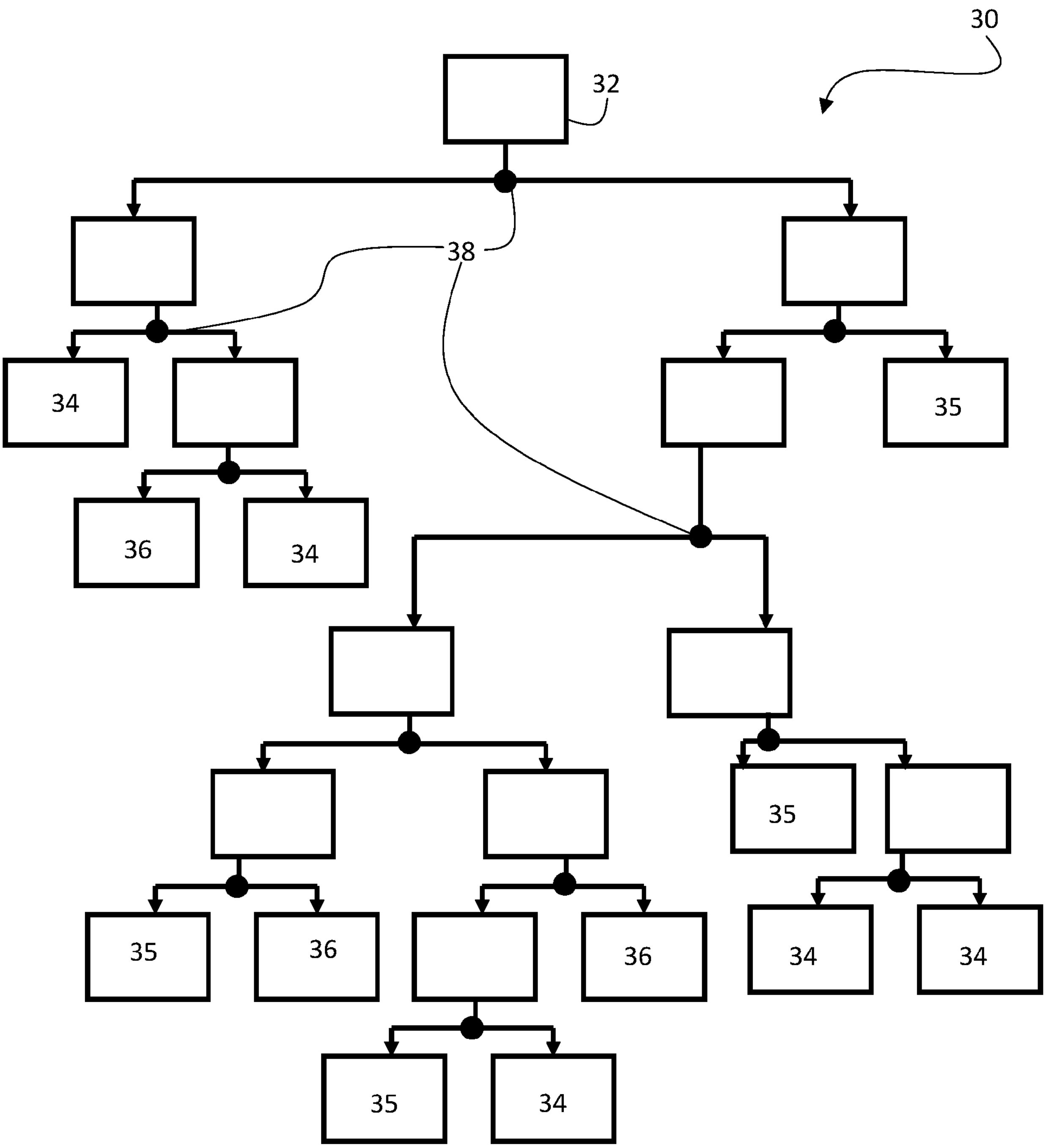

Figure 6

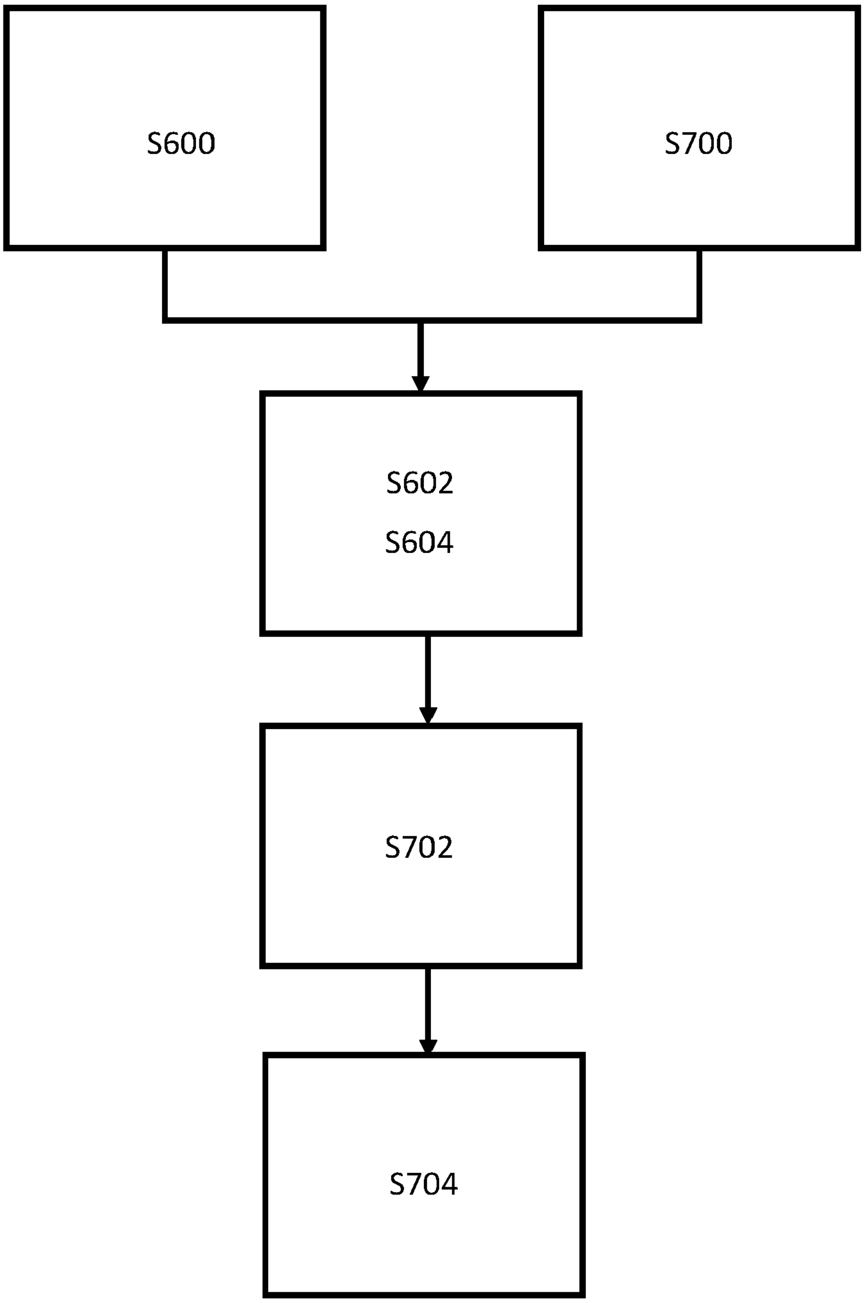

Figure 8

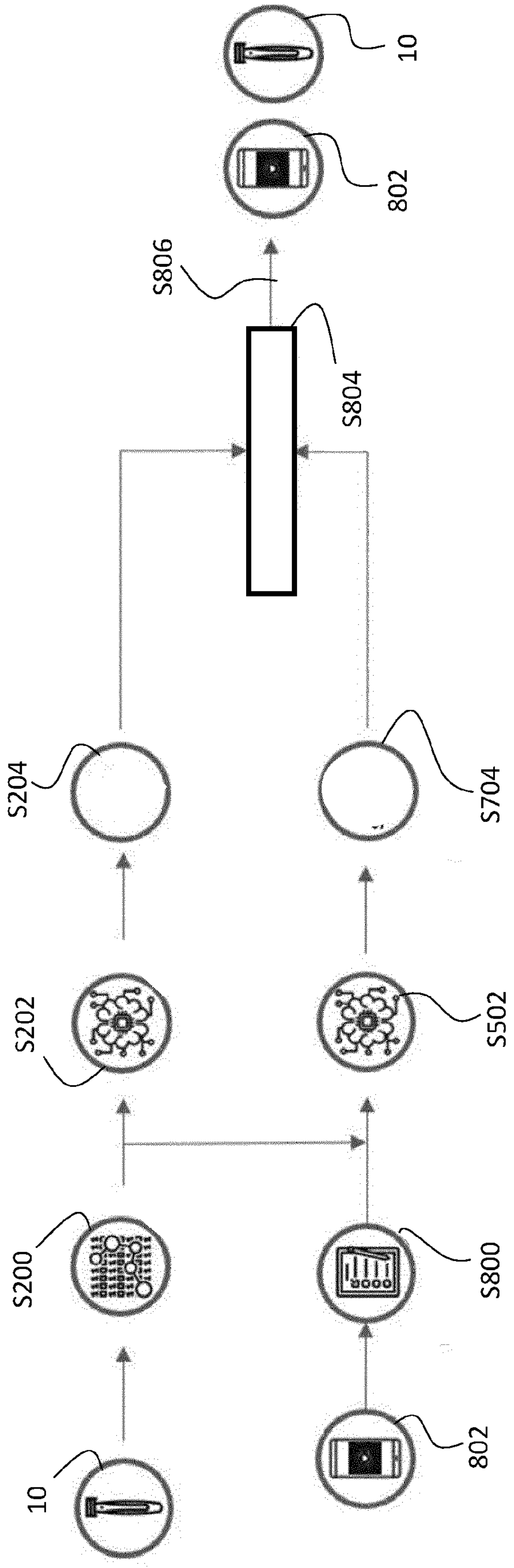

Figure 9

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EUROPEAN SEARCH REPORT

Application Number
EP 23 20 5003

DOCUMENTS CONSIDERED TO BE RELEVANT

Category	Citation of document with indication, where appropriate, of relevant passages	Relevant to claim	CLASSIFICATION OF THE APPLICATION (IPC)
X Y	WO 2021/262955 A1 (EDGEWELL PERSONAL CARE BRANDS LLC [US]) 30 December 2021 (2021-12-30) * paragraphs [0005], [0052], [0053], [0125] - [0136], [0169] - [0231] * * figures 1-7 * -----	1,5,6, 9-12,14, 15 2-4,13	INV. B26B19/38
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1

The present search report has been drawn up for all claims

Place of search	Date of completion of the search	Examiner
Munich	28 February 2024	Schouten, Adri

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