DESCRIPTION

Title:

DATA CORRECTION DEVICE, DATA CORRECTION METHOD, AND DATA CORRECTION PROGRAM

Technical Field

[0001] The present invention relates to a data correction device, a data correction method, and a data correction program.

Related Art

[0002] There are cases where a machine learning model is used to learn a relationship in time series data collected by a sensor or the like installed in a chemical plant or the like, and the model that has performed learning is used to perform anomaly sign detection or continuous calculation of characteristic values that are difficult to measure.

[0003] For example, in the case of anomaly sign detection, model learning for constructing a model that detects anomalies is performed. Accordingly, as a conventional technology, a technology is known in which fuzzy regression analysis is performed based on actual input and output values of multiple instrumentation devices, estimated values of input and output values of an instrumentation device as a monitor object are estimated, and a difference between the actual input and output values and the estimated values is displayed, thereby performing anomaly detection (for example, see Patent Document 1).

Prior Art Documents

Patent Documents

[0004] [Patent Document 1] Japanese Patent Laid-Open No. 2016-071456

SUMMARY

Technical Problem

[0005] However, in the above-described conventional technology, there are cases where it is difficult to execute inference with high accuracy when data drift occurs in time series data. For example, in the case where maintenance work or the like is performed on a data acquisition device or equipment targeted by the data acquisition device, data drift may occur in time series data acquired. In the case where data drift occurs in time series data, since a relationship between the time series data and a model that has completed learning changes, it is difficult to input the time series data after data drift to a model that has performed learning to perform inference using the time series data before drift and to perform inference with high accuracy. After data drift has occurred in time series data, it may take time to accumulate learning data for a model to relearn, and prompt model relearning may be difficult. As a result, it is difficult to continue inference with high accuracy.

Solution to Problem

[0006] Accordingly, to solve the above-described problems and achieve the object, a data correction device of the present invention is characterized by including: a correction amount calculation part, calculating a correction parameter using first data included in a reference section where an operation of equipment satisfies a predetermined condition in time series data before state change in equipment and second data included in the reference section in time series data after state change in equipment; a data transformation part, transforming the time series data after state change into being identical or similar to the time series data before state change, using the correction parameter calculated by the correction amount calculation part; and an inference part, inputting the time series data after state change transformed by the data transformation part to a model that has performed learning

using the time series data before state change in equipment, and performing inference.

Effects of Invention

[0007] According to the present invention, even if data drift occurs in time series data, it is possible to execute inference with high accuracy.

BRIEF DESCRIPTION OF THE DRAWINGS

[0008] FIG. 1 is a diagram describing an overview of processing by a data correction device according to an embodiment.

FIG. 2 is a diagram illustrating an example of a configuration of the data correction device according to an embodiment.

FIG. 3 is a table diagram illustrating an example of time series data according to an embodiment.

FIG. 4 is a table diagram illustrating an example of a reference section extraction condition according to an embodiment.

FIG. 5 is a table diagram illustrating an example of reference section data according to an embodiment.

FIG. 6 is a table diagram illustrating an example of transformed data according to an embodiment.

FIG. 7 is a diagram illustrating an example of data correction processing according to an embodiment.

FIG. 8 is a flowchart showing an example of a procedure of the data correction processing according to an embodiment.

FIG. 9 is a hardware configuration diagram illustrating an example of a computer that realizes a function of the data correction device according to an embodiment.

DESCRIPTION OF THE EMBODIMENTS

[0009] From here, an implementation mode (hereinafter referred to as "embodiment") will be described with reference to the drawings. In the following description, common components are given the same reference numerals, and repeated descriptions are omitted. The description of the embodiments given below does not limit the data correction device, data correction method, and data correction program according to the present invention.

[0010] <Introduction>

(Background)

In manufacturing equipment or the like, there are cases where an anomaly sign detection system or the like is constructed using a model that has learned a time series relationship acquired by a sensor or the like based on machine learning. Anomaly detection is performed based on the constructed model.

[0011] With respect to the manufacturing equipment or the like, there are cases where regular or sudden equipment maintenance such as cleaning of devices, zero point adjustment for sensors, overhaul, or replacement with normal products is implemented. When the above maintenance is implemented, there are cases where "data drift" occurs in which a relationship in time series data changes. Hereinafter, data drift is sometimes simply referred to as "drift."

[0012] In the case where the above-described drift occurs, since a relationship between the time series data and a model that has completed learning changes, even if the time series data after drift is input to a machine learning model that has performed learning to perform inference using the time series data before drift, it is difficult to perform inference with high accuracy.

[0013] Accordingly, there are cases where a method is implemented in which time series data are collected as learning data from the manufacturing equipment after

maintenance and the machine learning model performs relearning. However, to appropriately execute relearning, it is necessary to wait for accumulation of a sufficient amount of learning data, making it difficult to continue inference with respect to the occurrence of drift.

[0014] (Overview of Processing by Data Correction Device 100)

Accordingly, in a data correction device 100 according to the present embodiment, in the case where drift occurs due to maintenance, by correcting time series data (hereinafter sometimes referred to as "time series data after state change") after a state change in equipment using a correction parameter so that the time series data can be viewed as time series data (hereinafter sometimes referred to as "time series data before state change") before a state change in equipment, it is possible to perform inference using a machine learning model that has performed learning using the time series data before state change as it is.

[0015] Here, a series of flows of processing by the data correction device 100 will be described. FIG. 1 is a diagram describing an overview of processing by the data correction device 100 according to an embodiment. The data correction device 100 illustrated in FIG. 1 is an example of a computer that provides a technology for transforming the time series data after state change into data similar to the time series data before state change in order to appropriately perform inference using a machine learning model as it is without the machine learning model performing relearning.

[0016] In the time series data before state change acquired from the outside, data included in a reference section where an operation of equipment satisfies a predetermined condition is hereinafter sometimes simply referred to as "first data." In the time series data after state change acquired from the outside, data included in a reference section where an operation of equipment satisfies a predetermined condition is hereinafter sometimes simply

referred to as “second data.” The above-described “reference section” is a section where target equipment performs identical or similar operation before and after a state change, and corresponds to, for example, a data section showing the same behavior or a data section after stable operation of the equipment. The “machine learning model 10” illustrated in FIG. 1 is a model that has performed learning using the time series data before state change ((1) of FIG. 1).

[0017] First, in the data correction device 100, based on the first data extracted from the acquired time series data before state change and the second data extracted from the acquired time series data after state change, a correction parameter is calculated ((2) of FIG. 1). Next, in the data correction device 100, the time series data after state change is transformed so as to be identical or similar to the time series data before state change using the calculated correction parameter ((3) of FIG. 1).

[0018] In the data correction device 100, the time series data after state change transformed based on the correction parameter is input to the machine learning model 10, and inference is executed ((4) of FIG. 1). The data correction device 100 outputs an inference result as output data ((5) of FIG. 1).

[0019] As described above, in the data correction device 100 according to the present embodiment, by transforming the time series data after state change into the time series data before state change based on the calculated correction parameter, it is possible to perform inference using the machine learning model that has been used before the state change as it is, without performing relearning or reconstruction. That is, in the data correction device 100, execution of highly accurate inference using time series data in which drift has occurred is made possible, and an effect is achieved in which inference can be promptly continued even after drift occurs. An effect as follows is achieved. By using a model that has completed learning, the cost for model relearning is reduced. Even if data drift occurs,

inference can be resumed without waiting for accumulation of learning data.

[0020] <Description of Data Correction Device 100>

From here, detailed functions of the data correction device 100 according to the present embodiment will be described. FIG. 2 is a diagram illustrating an example of a configuration of the data correction device 100 according to an embodiment.

[0021] As illustrated in FIG. 2, the data correction device 100 includes a communication part 110, a storage part 120, and a control part 130. The data correction device 100 includes an input part (not illustrated) such as a keyboard or touch panel for receiving input from a user or the like, and a display part (not illustrated) such as a display or printer for displaying a result of information processing by the data correction device 100 to the user or the like.

[0022] (Communication Part 110)

The communication part 110 performs communication related to output of an inference result based on time series data (including time series data before state change, time series data after state change, first data, second data, and time series data after state change after transformation) and a machine learning model as well as input of time series data related to equipment. The communication part 110 may be realized by a network interface card (NIC) or the like. The communication part 110 can be connected to a network by wire or wirelessly as needed, and is capable of bidirectional transmission and reception of data.

[0023] (Storage Part 120)

The storage part 120 may be realized by, for example, a semiconductor memory element such as random access memory (RAM) or flash memory, or a storage device such as hard disk or optical disk. The storage part 120 stores data and programs used in various processings by the control part 130. As illustrated in FIG. 2, the storage part 120 includes a time series data database (DB) 121, a reference section extraction condition DB 122, a

reference section data DB 123, a transformed data DB 124, and a machine learning model DB 125.

[0024] (Time Series Data DB 121)

The time series data DB 121 is a database that stores time series data collected by an external data collection device such as a sensor. Here, an example of time series data stored by the time series data DB 121 will be described using FIG. 3. FIG. 3 is a table diagram illustrating an example of time series data according to an embodiment.

[0025] The time series data DB 121 stores "No" which is information for identifying data acquired in a time-series manner included in the time series data, in association with names of the acquired time series data, in table format as illustrated in FIG. 3 or the like. For example, as illustrated in FIG. 3, the time series data DB 121 stores time series data A "a" identified by No "1."

[0026] As illustrated in FIG. 3, the time series data DB 121 is able to store multiple pieces of time series data such as time series data A, time series data B, time series data C, and so on. "a, b, c…" illustrated in items of time series data A are data included in a target item, and may be information such as numerical values, text, and symbols.

[0027] The data stored in the time series data DB 121 is not limited to data in the table format illustrated in FIG. 3. For example, the time series data DB 121 is able to store measurement values obtained from multiple sensors, values calculated from sensor data, sequence numbers, flags representing an operating state of a device, or the like.

[0028] (Reference Section Extraction Condition DB 122)

The reference section extraction condition DB 122 is a database that stores a reference section extraction condition which is a condition for determining which section of the time series data corresponds to a reference section. Here, an example of reference section extraction condition stored by the reference section extraction condition DB 122 will be

described using FIG. 4. FIG. 4 is a table diagram illustrating an example of reference section extraction condition according to an embodiment.

[0029] The reference section extraction condition DB 122 stores "reference section conditions" which are conditions for determining whether a section is a reference section, in association with "No" and other information for identifying individual records, in table format as illustrated in FIG. 4 or the like.

[0030] From here, each individual reference section condition will be described. For example, the reference section extraction condition DB 122 stores "a portion of an operation implemented during equipment startup in a continuous process" as a reference section condition identified by No "1." The reference section condition identified by No "1" is a condition that a data section where an operation commonly executed during operation start (startup) of the equipment is executed in a continuous process of the equipment is set as a reference section.

[0031] The reference section extraction condition DB 122 stores "data of n cycles in a continuous process that implements cyclic operation" as a reference section condition identified by No "2." The reference section condition identified by No "2" is a condition that a data section corresponding to "n cycles" in cyclic operation in which the same operation is repeatedly executed in an equipment process is set as a reference section.

[0032] The reference section extraction condition DB 122 stores "data of n batches in a batch process" as a reference section condition identified by No "3." The reference section condition identified by No "3" is a condition that a data section corresponding to "n batches" in batch processing in an equipment process is set as a reference section.

[0033] (Reference Section Data DB 123)

The reference section data DB 123 is a database that stores, as reference section data, data extracted from acquired time series data based on a reference section condition. Here, an

example of reference section data stored by the reference section data DB 123 will be described using FIG. 5. FIG. 5 is a table diagram illustrating an example of reference section data according to an embodiment.

[0034] The reference section data DB 123 stores "No" which is information for identifying individual data included in the reference section data, in association with extracted reference section data (for example, first data and second data), in table format as illustrated in FIG. 5 or the like. For example, as illustrated in FIG. 5, the reference section data DB 123 stores first data "a1" in association with and identified by No "1."

[0035] As illustrated in FIG. 5, the reference section data DB 123 is able to store multiple pieces of time series data such as first data, second data, and so on. "a1, b1, c1 ....." illustrated in items of the first data are data included in a target item, and may be information such as numerical values, text, and symbols.

[0036] (Transformed Data DB 124)

The transformed data DB 124 is a database that stores, as transformed data, time series data after state change after transformation which is transformed based on a correction parameter. Here, an example of transformed data stored by the transformed data DB 124 will be described using FIG. 6. FIG. 6 is a table diagram illustrating an example of transformed data according to an embodiment.

[0037] The transformed data DB 124 stores "No" which is information for identifying individual data included in the transformed data, in association with the transformed data, in table format as illustrated in FIG. 6 or the like. For example, as illustrated in FIG. 6, the transformed data DB 124 stores transformed data "a2" in association with and identified by No "1."

[0038] (Machine Learning Model DB 125)

The machine learning model DB 125 is a database that stores a machine learning model

used for detecting anomaly signs or anomaly occurrence or for continuously calculating characteristic values that are difficult to measure, with time series data input thereto. For example, in the present embodiment, the machine learning model DB 125 stores a machine learning model that performs inference with the time series data before state change or the transformed data obtained by transforming time series data after state change based on a correction parameter input thereto.

[0039] The type of the machine learning model stored in the machine learning model DB 125 is not particularly limited. For example, the machine learning model DB 125 is able to store a machine learning model that has performed learning based on supervised learning, unsupervised learning, and reinforcement learning or the like, which are known technologies.

[0040] (Control Part 130)

The control part 130 is realized by a processor, micro processing unit (MPU), central processing unit (CPU) or the like executing various programs stored in the storage part 120 using a RAM as a working area. The control part 130 is realized by, for example, an integrated circuit (IC) such as application specific integrated circuit (ASIC) or field programmable gate array (FPGA).

[0041] As illustrated in FIG. 2, the control part 130 includes an acquisition part 131, an extraction part 132, a correction amount calculation part 133, a data transformation part 134, an inference part 135, an inverse transformation part 136, and an output part 137.

[0042] (Acquisition Part 131)

The acquisition part 131 acquires time series data collected based on equipment or a sensor or the like that monitors the equipment from a storage medium provided in the equipment or the sensor or the like, or from an external information processing device storing the time series data. The acquisition part 131 is able to store the acquired time series data in the

time series data DB 121.

[0043] (Extraction Part 132)

The extraction part 132 is able to extract data of a section corresponding to the "reference section" as reference section data from the time series data stored in the time series data DB 121, and store the reference section data in the reference section data DB 123.

[0044] For example, the extraction part 132 extracts, from the time series data, data corresponding to the reference section condition "a portion of an operation implemented during equipment startup in a continuous process" stored in the reference section extraction condition DB 122. The extraction part 132 is able to store data corresponding to the reference section of the time series data before state change as "first data" and data corresponding to the reference section of the time series data after state change as "second data" in the reference section data DB 123.

[0045] (Correction Amount Calculation Part 133)

The correction amount calculation part 133 calculates a correction parameter using the first data and the second data extracted by the extraction part 132. Specifically, the correction amount calculation part 133 compares the first data with the second data and calculates the correction parameter. From here, the calculation of the correction parameter based on the comparison between the first data and the second data will be described through a specific example.

[0046] For example, in the case where a state change in equipment occurs due to drift of a center position of data distribution which is a predetermined reference point, the correction amount calculation part 133 calculates a difference value between the center position of data distribution in the first data and the center position of data distribution in the second data as a correction parameter (correction value). For example, the correction amount calculation part 133 compares the center positions of data distribution between the

first data which is time series data before state change due to maintenance and the second data which is time series data after state change due to maintenance, and calculates a difference therebetween as a correction parameter (correction value).

[0047] For example, in the case where a state change in equipment occurs due to calibration of a position of a zero point which is a predetermined reference point, the correction amount calculation part 133 calculates a value changed by calibration as a correction parameter. The above example is a correction parameter used in the case where a variation of the zero point of equipment (sensor) due to maintenance is corrected. That is, the correction amount calculation part 133 compares the positions of the zero point between the first data which is time series data before state change due to maintenance and the second data which is time series data after state change due to maintenance, and calculates a difference therebetween as a correction parameter (correction value).

[0048] Here, the calculation of the correction parameter in a "case where calibration is performed based on bias" and a "case where calibration is performed based on gain and bias" will be described.

[0049] The calibration based on bias can be expressed by Expression (1) which is a correction function (correction method) shown below.

[0050] $f(x)=x+b$ …(1)

f(x): correction function

x: time series data

b: correction parameter calculated from bias change

[0051] In the case where calibration is performed based on bias, the correction amount calculation part 133 compares the average values of the time series data before and after state change, and calculates a correction parameter (for example, "b") included in Expression (1). Specifically, the correction amount calculation part 133 substitutes the

average value (mean(X1)) of the first data and the average value (mean(X2)) of the second data into Expression (2) shown below and calculates the correction parameter.

[0052] b=mean(X1)−mean(X2) …(2)

mean(X1): average value of first data

mean(X2): average value of second data

[0053] On the other hand, the calibration based on gain and bias can be expressed by Expression (3) which is a correction function (correction method) shown below.

[0054] f(x)=a*x+b …(3)

f(x): correction function

x: time series data

a: correction parameter calculated from gain change

b: correction parameter calculated from bias change

[0055] In the case where calibration is performed based on gain and bias, the correction amount calculation part 133 calculates a correction parameter (for example, “a” and “b”) based on a value implemented in correction that caused a state change.

[0056] For example, it is assumed that, in work that caused a state change, correction is performed so that the zero point becomes “+z” and the gain becomes “g times.” In that case, the correction amount calculation part 133 calculates the correction parameters “a” and “b” in Expression (3) based on Expressions (4) and (5) below.

[0057] a=1/g …(4)

b=−z …(5)

[0058] (Data Transformation Part 134)

The data transformation part 134 transforms the time series data after state change into being identical or similar to the time series data before state change using the correction parameter calculated by the correction amount calculation part 133. The data transformation part 134

is able to store the transformed time series data after state change after transformation in the transformed data DB 124.

[0059] Specifically, the data transformation part 134 transforms the time series data after state change into data that is identical or similar to the time series data before state change using the correction parameter calculated by the correction amount calculation part 133 and a correction expression.

[0060] For example, in the case where calibration is performed based on bias, the data transformation part 134 is able to transform the time series data after state change into data that is identical or similar to the time series data before state change in accordance with Expression (1), using the correction parameter calculated based on Expression (2) and the time series data x after state change.

[0061] In the case where calibration is performed based on gain and bias, the data transformation part 134 is able to transform the time series data after state change into data that is identical or similar to the time series data before state change in accordance with Expression (3), using the correction parameter calculated based on the Expressions (4) and (5) and the time series data x after state change.

[0062] (Inference Part 135)

The inference part 135 inputs the time series data after state change after transformation transformed by the data transformation part 134 to a machine learning model that has performed learning using the time series data before state change, and performs inference. In the present embodiment, “inference” includes detection of anomaly signs or anomaly occurrence based on input time series data, calculation of characteristic values, or the like.

[0063] For example, the inference part 135 inputs the time series data after state change after transformation to a machine learning model that has performed learning based on a relationship in the time series data before state change, and executes inference such as

detection of anomaly signs or anomaly occurrence, calculation of characteristic values, or the like.

[0064] (Inverse Transformation Part 136)

The inverse transformation part 136 transforms (inversely transforms), using a correction parameter, a result inferred by the inference part 135 using the time series data after state change after transformation into being identical or similar to a result inferred using the time series data after state change before transformation.

[0065] For example, in the case where calibration is performed based on bias, the inverse transformation part 136 is able to apply an inference result obtained by inputting the time series data after state change after transformation to the machine learning model to Expression (6), thereby correcting the inference result.

[0066] $f(x)=x-b$ …(6)

f(x): (inverse) correction function

x: inference result from machine learning model

b: parameter calculated by Expression (2)

[0067] For example, in the case where calibration is performed based on gain and bias, the inverse transformation part 136 is able to apply an inference result obtained by inputting the time series data after state change after transformation to the machine learning model to Expression (7), thereby correcting the inference result.

[0068] $f(x)=1/a*x-b/a$ …(7)

f(x): (inverse) correction function

x: inference result from machine learning model

a: parameter calculated by Expression (4)

b: parameter calculated by Expression (5)

[0069] In addition, the inverse transformation part 136 compares an inference result

using the time series data before state change with an inference result using the time series data after state change after transformation, and calculates a correction parameter for inverse transformation so that an inference result based on the time series data after state change after transformation is identical or similar to an inference result based on the time series data before state change. The inverse transformation part 136 is able to correct the inference result based on the time series data after state change after transformation to an appropriate inference result after state change, using the calculated correction parameter for inverse transformation.

[0070] The processing by the inverse transformation part 136 may be executed in the case of satisfying preset conditions such as target equipment, operating conditions, surrounding environment, and use of the machine learning model. In the case of not satisfying the conditions, the processing by the inverse transformation part 136 may not be executed.

[0071] (Output Part 137)

The output part 137 outputs an inference result by the inference part 135 to an information processing device or the like operated by a target user. The output part 137 is able to output the inference result inversely transformed by the inverse transformation part 136 to the information processing device or the like operated by the target user.

[0072] (Example of Processing)

From here, data correction processing realized by the data correction device 100 according to the present embodiment will be described using FIG. 7. FIG. 7 is a diagram illustrating an example of data correction processing according to an embodiment.

[0073] The example illustrated in FIG. 7 is an example of processing by the data correction device 100 in the case where drift occurs due to equipment maintenance being implemented or the like when the time series data before state change is input to the machine

learning model 11 and inference is performed, and it is difficult to perform inference with high accuracy.

[0074] First, the data correction device 100 (acquisition part) acquires time series data (input data) collected by equipment or a sensor or the like, and stores the time series data in the storage part 120 (time series data DB) ((1) of FIG. 7).

[0075] In the data correction device 100 (correction amount calculation part), the first data (data corresponding to a reference section in the time series data before state change due to maintenance) and the second data (data corresponding to a reference section in the time series data after state change due to maintenance) are extracted from the time series data stored in the storage part 120 (time series data DB) ((2) of FIG. 7).

[0076] In the data correction device 100 (correction amount calculation part), a correction parameter is calculated ((3) of FIG. 7). Specifically, in the data correction device 100 (correction amount calculation part), the first data is compared with the second data, and the correction parameter is calculated ((3-1) of FIG. 7).

[0077] In the data correction device 100 (data transformation part), data transformation is performed using the calculated correction parameter ((4) of FIG. 7). Specifically, in the data correction device 100 (data transformation part), transformation is performed using the correction parameter ((3-1) of FIG. 7), so that the time series data after state change ((4-1) of FIG. 7) becomes the same data as the time series data before state change ((4-2) of FIG. 7).

[0078] In the data correction device 100 (inference part), the time series data after state change after transformation is input to the machine learning model 11, and inference is implemented ((5-1) of FIG. 7). The data correction device 100 (output part) outputs to a user or the like an inference result based on the time series data after state change after transformation ((5-2) of FIG. 7).

[0079] In the case where a condition for implementing inverse transformation on an inference result (after transformation) is satisfied, in the data correction device 100 (inverse transformation part), inverse transformation processing is executed on the inference result ((6-1) of FIG. 7) based on the time series data after state change after transformation ((6-2) of FIG. 7). The data correction device 100 (output part) outputs to the user or the like an inference result (after inverse transformation) generated based on the inverse transformation processing ((6-3) of FIG. 7).

[0080] (Processing Procedure)

From here, a procedure of processing by the data correction device 100 according to the present embodiment will be described using FIG. 8. FIG. 8 is a flowchart showing an example of the procedure of data correction processing according to an embodiment.

[0081] The data correction device 100 waits for processing until an event (for example, regular maintenance) having a possibility of occurrence of data drift occurs (No in S101). Then, if an event having the possibility occurs (Yes in S101), the data correction device 100 starts the processing.

[0082] First, the acquisition part 131 acquires time series data from the outside (S102). Next, the extraction part 132 extracts, as reference section data, the first data before state change and the second data after state change, from the time series data before and after state change stored in the time series data DB, as described above (S103).

[0083] The correction amount calculation part 133 calculates a correction parameter using the extracted reference section data (first data and second data) (S104). Next, the data transformation part 134 transforms the time series data after state change using the calculated correction parameter (S105).

[0084] The inference part 135 executes inference using the time series data after state change after transformation (S106). Here, if an execution condition for inverse

transformation is satisfied (Yes in S107), the inverse transformation part 136 executes inverse transformation on an inference result (S108). On the other hand, if the execution condition for inverse transformation is not satisfied (No in S107), the data correction device 100 skips the processing of S108.

[0085] The output part 137 outputs the inference result based on the transformed data or the inference result after inverse transformation (S109). Then, the data correction device 100 ends the processing.

[0086] (Effects)

From here, effects achieved by the data correction device 100 according to the present embodiment will be described. Conventionally, in the case where maintenance of equipment or a sensor or the like is implemented and drift occurs, since a relationship between time series data and a machine learning model that has completed learning changes, there is a problem that it is difficult to perform inference with high accuracy by using the machine learning model that has performed learning before drift as it is.

[0087] Accordingly, the correction amount calculation part 133 of the data correction device 100 according to the present embodiment calculates a correction parameter using the first data and the second data. The data transformation part 134 of the data correction device 100 transforms the time series data after state change into being identical or similar to the time series data before state change using the correction parameter calculated by the correction amount calculation part 133. The inference part 135 of the data correction device 100 inputs the time series data after state change after transformation transformed by the data transformation part 134 to the machine learning model that has performed learning using the time series data before state change and performs inference.

[0088] Through the processing described above, the data correction device 100 of the present embodiment achieves an effect that execution of highly accurate inference using

time series data in which drift has occurred is made possible.

[0089] For example, in the data correction device 100, in the case where drift occurs, by correcting data after drift using the correction parameter so that the data can be viewed as data before drift, it is possible to perform inference using the machine learning model created before drift as it is. Hence, in the data correction device 100, man-hours and computer resources for relearning or reconstruction of the machine learning model can be reduced.

[0090] In addition, the data correction device 100 achieves the effects described below. Specifically, the inverse transformation part 136 transforms (inversely transforms), using the correction parameter, a result inferred by the inference part 135 using the time series data after state change after transformation into being identical or similar to a result inferred using the time series data after state change before transformation.

[0091] In the case where the gain (magnification) and zero point of a measuring instrument are calibrated through maintenance, the inverse transformation part 136 is able to correct an inference result based on the time series data after state change after transformation to an appropriate inference result after state change.

[0092] Through the processing described above, in the data correction device 100, inverse transformation can be performed so that the obtained inference result becomes similar to the inference result performed using the time series data after state change. Hence, the data correction device 100 achieves an effect that implementation of inference with high accuracy is made possible without the machine learning model performing relearning even after a state change in equipment or the like.

[0093] The correction amount calculation part 133 compares the first data with the second data, and calculates a difference value of a predetermined reference point as the correction parameter. In the data correction device 100, the correction parameter, which

is used to transform the time series data after state change into data similar to the time series data before state change, can be calculated according to a cause of drift.

[0094] For example, in the case where a state change in equipment occurs due to calibration of the position of the zero point which is a predetermined reference point, the correction amount calculation part 133 calculates a value changed by calibration as the correction parameter. Through the processing described above, in the data correction device 100, even if the zero point shifts due to equipment maintenance or the like, the correction parameter for performing data transformation corresponding to the event can be calculated.

[0095] For example, in the case where a state change in equipment occurs due to drift of the center position of data distribution which is a predetermined reference point, the correction amount calculation part 133 calculates the difference value between the center position of data distribution in the first data and the center position of data distribution in the second data as the correction parameter. Through the processing described above, in the data correction device 100, even if a median value of data shifts due to equipment maintenance or the like, the correction parameter for performing data transformation corresponding to the event can be calculated.

[0096] As a result, the data correction device 100 achieves an effect that execution of highly accurate inference using time series data in which drift has occurred is realized by enabling appropriate response to various causes of drift.

[0097] In the case where the gain (magnification) and zero point of a measuring instrument are calibrated through maintenance, the correction amount calculation part 133 calculates a predetermined coefficient as the correction parameter from an adjustment amount of gain. The data transformation part 134 corrects the time series data after state change using the predetermined coefficient calculated from the adjustment amount of gain.

[0098] Through the processing described above, in the data correction device 100, a calibration amount (for example, “ratio of a value before and after calibration” in the case of gain and “difference before and after calibration” in the case of shift amount) of gain or shift amount or the like of an AD converter or the like can be used as a correction parameter as it is. As a result, the data correction device 100 enables efficient transformation of time series data.

[0099] The data transformation part 134 transforms the time series data after state change into data that is identical or similar to the time series data before state change using the correction parameter calculated by the correction amount calculation part 133 and a correction expression.

[0100] Through the processing described above, in the data correction device 100, even if drift occurs due to equipment maintenance or the like, by transforming the time series data after state change into being similar to the time series data before state change, inference can be implemented utilizing a machine learning model that has been used so far as it is. As a result, in the data correction device 100, there is no need for the machine learning model to perform relearning, man-hours or resources can be reduced, and inference of anomaly signs or anomaly occurrence and characteristic values can be continued without stopping the operation of equipment or the like.

[0101] <Modifications>

The following describes modifications realized by the data correction device 100 according to the present embodiment.

[0102] (Data, or the Like)

The time series data before state change, time series data after state change, first data, second data, correction parameter, inference result, inverse transformation, names of functional parts of the data correction device 100, steps, processes, names of steps or processes, or the

like used in the above description of embodiments are merely examples and can be arbitrarily changed.

[0103] The storage part 120 of the data correction device 100 according to the present embodiment has been described as storing target data or information in table format, but is not limited thereto. For example, the storage part 120 is able to store target data or information in a format such as predetermined file or image, in addition to table format.

[0104] For example, the time series data DB 121 has been described as storing "No" which is information for identifying data acquired in a time-series manner included in the time series data in association with the names of the acquired time series data in table format as illustrated in FIG. 3. However, the table items or content included in the items are not limited to the content illustrated in FIG. 3.

[0105] The reference section extraction condition DB 122 has been described as storing "reference section condition" which is a condition for determining whether it is a reference section, in association with "No" or the like which is information for identifying individual records, in table format as illustrated in FIG. 4. However, the table items or content included in the items are not limited to the content illustrated in FIG. 4.

[0106] The reference section data DB 123 has been described as storing "No" which is information for identifying individual data included in reference section data, in association with the extracted reference section data (for example, first data and second data), in table format as illustrated in FIG. 5. However, the table items or content included in the items are not limited to the content illustrated in FIG. 5.

[0107] The transformed data DB 124 has been described as storing "No" which is information for identifying individual data included in transformed data, in association with the transformed data (for example, time series data after state change (after transformation)), in table format as illustrated in FIG. 6. However, the table items or content included in the

items are not limited to the content illustrated in FIG. 6.

[0108] (Application Field, or the Like)

The data correction device 100 according to the present embodiment can be applied to various fields such as semiconductor manufacturing processes and water treatment equipment, such as chemical plants, chemical processes, power plant facilities, and machining processes (such as presses and numerically controlled (NC) machine tools/machining centers (MCs)). The application fields described above are merely examples, and the application field of the data correction device 100 according to the present embodiment is not limited thereto.

[0109] (Flowchart, or the Like)

Each step in the flowcharts or the like may be rearranged and implemented as long as there are no contradictions, or there may be steps that are not implemented. Conjunctions such as “next,” “subsequently,” “furthermore,” “at this time,” and “on this occasion” in the description of the flowcharts do not limit the order or timing of the implementation of processings in the flowcharts.

[0110] (Others)

Among the processings described in the above embodiments and modifications, all or some of the processings described as being automatically performed can also be manually performed, or all or some of the processings described as being manually performed can also be automatically performed by a known method. The processing procedures, specific names, and information including various data or parameters illustrated in the above document or drawings can be arbitrarily changed unless otherwise specified. For example, the various information illustrated in each drawing is not limited to the information illustrated in the drawings.

[0111] Each component of each device illustrated in the drawings is a functional

concept and does not necessarily need to be physically configured as illustrated in the drawings. That is, the specific form of distribution or integration of each device is not limited to that illustrated in the drawings, and all or some of the components can be configured to be functionally or physically distributed or integrated in arbitrary units according to various loads, usage conditions, or the like.

[0112] The above-described components include those that can be easily assumed by those skilled in the art, those that are substantially identical, and those within a so-called range of equivalents. Furthermore, the above-described embodiments and modifications can be appropriately combined within a range in which the processing contents do not contradict.

[0113] The "part (section, module, unit)" as used above can be read as "means" or "circuit," or the like. For example, a control part can be read as a control means or control circuit.

[0114] While several embodiments have been described in detail based on the drawings, these are examples, and the present embodiment can be implemented in other forms with various modifications and improvements applied therein based on the knowledge of those skilled in the art, including the aspects described in the disclosure of the invention.

[0115] <Hardware Configuration>

The data correction device 100 according to the present embodiment is realized by, for example, a computer 1000 having a configuration as illustrated in FIG. 9. FIG. 9 is a hardware configuration diagram illustrating an example of a computer that realizes the functions of the data correction device 100 according to an embodiment. The computer 1000 is in a form in which a CPU 1100, a RAM 1200, a ROM 1300, an auxiliary storage device 1400, a communication interface (I/F) 1500, and an input/output I/F 1600 are

connected via a bus 1800.

[0116] The CPU 1100 operates based on a program stored in the ROM 1300 or the auxiliary storage device 1400 and controls each part. The ROM 1300 stores a boot program executed by the CPU 1100 at the startup of the computer 1000 or a program dependent on the hardware of the computer 1000.

[0117] The auxiliary storage device 1400 stores a program executed by the CPU 1100 and data used by the program. The communication I/F 1500 receives data from other devices via a predetermined communication network NW (including wireless communication in a closed area in the present embodiment), transmits the data to the CPU 1100, and transmits data generated by the CPU 1100 to other devices via the predetermined communication network NW. The CPU 1100 controls an output device such as a display or printer and an input/output device 1700 such as a keyboard or mouse via the input/output I/F 1600. The CPU 1100 acquires data from the input/output devices 1700 via the input/output I/F 1600. The CPU 1100 outputs generated data to the input/output devices 1700 via the input/output I/F 1600.

[0118] For example, in the case where the computer 1000 functions as various devices according to the present embodiment, the CPU 1100 of the computer 1000 realizes the function of the control part by executing a program loaded on the RAM 1200.

Description of Reference Numerals

[0119] 100: data correction device

110: communication part

120: storage part

121: time series data DB

122: reference section extraction condition DB

123: reference section data DB

124: transformed data DB

125: machine learning model DB

130: control part

131: acquisition part

132: extraction part

133: correction amount calculation part

134: data transformation part

135: inference part

136: inverse transformation part

137: output part

CLAIMS

Claim 1:

A data correction device comprising:

a correction amount calculation part, calculating a correction parameter using first data included in a reference section where an operation of equipment satisfies a predetermined condition in time series data before state change in equipment and second data included in the reference section in time series data after state change in equipment;

a data transformation part, transforming the time series data after state change in equipment into being identical or similar to the time series data before state change in equipment, using the correction parameter calculated by the correction amount calculation part; and

an inference part, inputting the time series data after state change in equipment after transformation transformed by the data transformation part to a model that has performed learning using the time series data before state change in equipment, and performing inference.

Claim 2:

The data correction device according to claim 1, further comprising:

an inverse transformation part, transforming a result inferred using the time series data after state change in equipment after transformation into being identical or similar to a result inferred using time series data after state change in equipment before transformation, using the correction parameter.

Claim 3:

The data correction device according to claim 1 or 2, wherein

the correction amount calculation part compares the first data with the second data and calculates the correction parameter.

Claim 4:

The data correction device according to claim 3, wherein

in a case where a state change in equipment occurs due to calibration of a position of a zero point, the correction amount calculation part calculates a value changed by the calibration as the correction parameter.

Claim 5:

The data correction device according to claim 3, wherein

in a case where a state change in equipment occurs due to drift of a center position of data distribution, the correction amount calculation part calculates a difference value between a center position of data distribution in the first data and a center position of data distribution in the second data as the correction parameter.

Claim 6:

The data correction device according to claim 1 or 2, wherein

the data transformation part transforms time series data after state change in equipment into being identical or similar data to the time series data before state change in equipment using the correction parameter calculated by the correction amount calculation part and a correction expression.

Claim 7:

A data correction method executed by a data correction device, comprising:

a correction amount calculation process, in which a correction parameter is calculated using first data included in a reference section where an operation of equipment satisfies a predetermined condition in time series data before state change in equipment and second data included in the reference section in time series data after state change in equipment;

a data transformation process, in which the time series data after state change in equipment is transformed into being identical or similar to the time series data before state change in equipment, using the correction parameter calculated by the correction amount calculation process; and

an inference process, in which the time series data after state change in equipment after transformation transformed by the data transformation process is input to a model that has performed learning using the time series data before state change in equipment, and interference is performed.

Claim 8:

A data correction program, causing a computer to execute:

a correction amount calculation procedure, in which a correction parameter is calculated using first data included in a reference section where an operation of equipment satisfies a predetermined condition in time series data before state change in equipment and second data included in the reference section in time series data after state change in equipment;

a data transformation procedure, in which the time series data after state change in equipment is transformed into being identical or similar to the time series data before state change in equipment, using the correction parameter calculated by the correction amount calculation procedure; and

an inference procedure, in which the time series data after state change in equipment after transformation transformed by the data transformation procedure is input to a model that has performed learning using the time series data before state change in equipment, and interference is performed.

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