METHOD AND APPARATUS FOR CONSTRUCTING BEHAVIOR TREND MODEL, DEVICE, AND BEHAVIOR DEVIATION DETECTION METHOD

TECHNICAL FIELD

[0001] The present disclosure relates to the technical field of smart homes, and in particular, to a method and apparatus for constructing a behavior trend model, a device, and a behavior deviation detection method.

BACKGROUND

[0002] With the iterative upgrading of smart home, artificial intelligence, and Internet of Things technologies, a diverse range of smart devices, such as smart cameras, sweeping robots, smart speakers, and millimeter-wave radars, have become deeply integrated into household scenarios. In order to optimize user's living experience, coordinated linkage between devices has become a core path for improving the level of household intelligence.

[0003] Generally, a smart camera may collect visual data of a household scene, a millimeter-wave radar may accurately perceive motion and position information of a human body, a smart speaker may serve as a human-machine interaction terminal to receive instructions and provide feedback information, and an environment sensor may monitor environmental parameters such as temperature, humidity, and smoke in real time. When a certain device detects an abnormal signal that meets a preset threshold, for example, when a camera captures an image feature corresponding to an elderly person falling, an intelligent hub pushes alert information to a user via a smart speaker.

[0004] However, in the collaboration process of the above devices, the existing systems can only trigger a response mechanism after a clear dangerous event has occurred, and are unable to capture an evolution process and precursor behaviors before a risk is formed, thereby reducing the risk prevention and control efficiency of a

household smart system.

SUMMARY

[0005] In order to solve the above technical problems, the present disclosure provides a method and apparatus for constructing a behavior trend model, a device, and a behavior deviation detection method, so as to solve the technical problem that the existing household smart care technologies are unable to recognize a risk evolution process, making it difficult to achieve proactive prevention.

[0006] According to a first aspect of the present disclosure, a method for constructing a behavior trend model is provided. The method includes: performing association processing on behavior data sets of a plurality of users to obtain standard behavior data subsets corresponding to the users; dividing the standard behavior data subsets into a plurality of behavior chains based on a preset behavior association rule, the behavior chains being used for combining behavior data in the standard behavior data subsets to form a complete behavior process; determining a stability data set of the behavior chains based on a monitoring period; and constructing the behavior trend model based on the stability data set.

[0007] According to a second aspect of the present disclosure, a behavior deviation detection method is provided. The behavior deviation detection method includes: acquiring a behavior data set of users; determining the behavior data set as a plurality of behavior chains based on a behavior trend model; and calculating a deviation degree of each behavior chain, and outputting warning information in a case where the deviation degree is greater than a preset threshold.

[0008] According to a third aspect of the present disclosure, an apparatus for constructing a model based on a behavior trend is provided. The apparatus includes: a data processing module, configured to perform association processing on behavior data sets of a plurality of users to obtain standard behavior data subsets corresponding to the users; a data classification module, configured to divide the standard behavior data subsets into a plurality of behavior chains based on a preset behavior association rule, the behavior chains being used for combining behavior data in the standard behavior

data subsets to form a complete behavior process; and a model construction module, configured to determine a stability data set of the behavior chains based on a monitoring period, and construct a behavior trend model based on the stability data set.

[0009] According to a fourth aspect of the present disclosure, a computer-readable storage medium is provided. The storage medium is configured to store a computer program therein, the computer program being used for performing the method for constructing the behavior trend model according to the first aspect.

[0010] According to a fifth aspect of the present disclosure, an electronic device is provided. The electronic device includes: a processor; a memory, configured to store instructions executable by the processor, wherein the processor is configured to read the executable instructions from the memory and execute the instructions to implement the method for constructing the behavior trend model according to the first aspect.

[0011] According to a sixth aspect of the present disclosure, a computer program product is provided, which, when instructions in the computer program product are executed by a processor, performs the method for constructing the behavior trend model provided by the embodiments of the first aspect of the present disclosure.

[0012] With the technical solutions provided by the embodiments of the present disclosure, a plurality of items of behavior data in the behavior data set are subjected to corresponding association processing with different users, such that standard behavior data related to each user can be determined for this user, and discrete behavior data points of each user are then combined into coherent behavior chains based on a behavior association rule, such that different behavior chains of each user can be determined. On this basis, by analyzing the stability of the behavior chains within the monitoring period, a personalized long-term behavior trend model can be established for each user; and by comparing the current behavior chain with the personalized long-term behavior trend model in real time, subtle deviations in terms of time, space, frequency, or behavior sequence can be sensitively detected, and a reminder or an alarm can be sent to a family member or a guardian based on each deviation, thereby making it possible to understand the formation of a risk in a smart home environment and to achieve early and accurate risk alert, thereby improving the accuracy of risk

recognition and the response efficiency of household smart care for different members.

BRIEF DESCRIPTION OF DRAWINGS

[0013] FIG. 1 is a behavior trend evaluation system according to an exemplary embodiment of the present disclosure.

[0014] FIG. 2 is a schematic flowchart of a method for constructing a behavior trend model according to an exemplary embodiment of the present disclosure.

[0015] FIG. 3 is a schematic flowchart of a method for constructing a behavior trend model according to another exemplary embodiment of the present disclosure.

[0016] FIG. 4 is a schematic flowchart of a method for constructing a behavior trend model according to another exemplary embodiment of the present disclosure.

[0017] FIG. 5 is a schematic flowchart of a method for constructing a behavior trend model according to another exemplary embodiment of the present disclosure.

[0018] FIG. 6 is a schematic flowchart of a method for constructing a behavior trend model according to another exemplary embodiment of the present disclosure.

[0019] FIG. 7 is a schematic flowchart of a method for constructing a behavior trend model according to another exemplary embodiment of the present disclosure.

[0020] FIG. 8 is a schematic flowchart of a method for constructing a behavior trend model according to another exemplary embodiment of the present disclosure.

[0021] FIG. 9 is a schematic flowchart of a method for constructing a behavior trend model according to another exemplary embodiment of the present disclosure.

[0022] FIG. 10 is a schematic flowchart of a method for constructing a behavior trend model according to another exemplary embodiment of the present disclosure.

[0023] FIG. 11 is a schematic structural diagram of an apparatus for constructing a behavior trend model according to another exemplary embodiment of the present disclosure.

[0024] FIG. 12 is a structural diagram of an electronic device provided by an exemplary embodiment of the present disclosure.

DESCRIPTION OF EMBODIMENTS

[0025] In order to explain the present disclosure, exemplary embodiments of the present disclosure will be described in detail below with reference to the accompanying drawings. It is apparent that the described embodiments are merely some, rather than all, of the embodiments of the present disclosure. It should be understood that the present disclosure is not limited by the exemplary embodiments.

[0026] It should be noted that, unless otherwise specifically stated, the relative arrangement, numerical expressions, and numerical values of the components and steps set forth in these embodiments do not limit the scope of the present disclosure.

[0027] Overview of the Application

[0028] In the related art, in a smart home system, a smart camera may collect visual data of a household scene, a millimeter-wave radar may accurately perceive motion and position information of a human body, a smart speaker may serve as a human-machine interaction terminal to receive instructions and provide feedback information, and various environment sensors may monitor environmental parameters such as temperature, humidity, and smoke concentration in real time. When any perception device detects a trigger signal that meets a preset abnormality threshold, for example, when a smart camera captures image information that conforms to a fall feature, a smart home hub system pushes alert information to a user via a preset terminal. However, a risk alert mechanism of the related art can only trigger a passive response for a clear dangerous event that has already occurred, and is unable to capture and recognize an evolution path and precursor behaviors in the process of risk formation, resulting in the risk prevention and control efficiency of the household smart care system being unable to meet actual needs.

[0029] With the technical solutions provided by the embodiments of the present disclosure, user identity association processing is performed on a plurality of items of behavior data in a behavior data set, to obtain standard behavior data subsets in one-to-one correspondence to each user; discrete behavior data points in the standard behavior data subsets are sequentially aggregated based on a preset behavior association rule, to generate a plurality of behavior chains corresponding to different behavior processes; and a stability feature of each behavior chain is analyzed based on

a preset monitoring period, to construct, for each user, a personalized long-term behavior trend model that matches user's behavior habits.

[0030] Based on the behavior trend model, the current behavior chain obtained through real-time collection is compared and computed with the personalized long-term behavior trend model, so that subtle deviations of the current behavior in terms of a time dimension, a space dimension, an occurrence frequency, and a behavior sequence level can be sensitively detected; and when a degree of deviation satisfies a preset trigger condition, reminder or alarm information is sent to a family member or a preset guardian. By means of the behavior deviation detection method, the present disclosure is able to achieve behavior perception of the process of risk formation in a smart home scenario, and achieve early and accurate risk alert effects, thereby effectively improving the accuracy of risk recognition and response efficiency of household smart care for different individual family members.

[0031] Exemplary System

[0032] FIG. 1 shows a schematic architectural diagram of a behavior trend evaluation system 100 according to an exemplary embodiment of the present disclosure. As shown in FIG. 1, the system 100 may include an electronic device 110, a server 120, and a database 130.

[0033] The electronic device 110 is configured to receive data from a perception module and a terminal device, wherein the perception module may be integrated on the terminal device, or may exist independently. For example, the perception module may be a millimeter-wave radar, a human infrared sensor, a high-definition camera module, or the like; and the terminal device may be a smart camera, a sweeping robot, a smart door lock, a smart speaker, or the like.

[0034] After completing collection alignment and format preprocessing of raw data, the electronic device 110 sends a standardized behavior data set to the server 120, and is also configured to push warning information to a designated user in response to an instruction from the server 120.

[0035] The server 120 is configured to construct and store a behavior trend model, and calculate a behavior deviation result according to the behavior trend model.

Specifically, the server 120 executes: user identity association processing, in which multi-source behavior data are bound one-to-one with different users to obtain a corresponding standard behavior data subset; sequential aggregation of discrete behavior data points based on a preset behavior association rule, to generate a behavior chain corresponding to a complete behavior process; and analysis of the stability features of the behavior chains based on a monitoring period, to construct a personalized long-term behavior trend model for the users.

[0036] In a real-time monitoring stage, the current behavior chain is compared with the behavior trend model, a comprehensive deviation degree in four dimensions, namely a time dimension, a space dimension, a behavior frequency, and a behavior sequence, is calculated; whether the deviation degree satisfies an alert trigger condition is determined; and if so, an alarm instruction is generated and delivered to the electronic device 110, and at the same time, intermediate data, model parameters, and results generated by all computations are stored in the database 130.

[0037] The database 130 is configured to store, in a layered manner, raw behavior collection data, the standard behavior data subsets associated with the users, the behavior chain data generated by aggregation, the personalized behavior trend model parameters, and result logs of previous behavior deviation detections, so as to support the server 120 in calling historical data at any time for model iterative updating and deviation result retrospective verification, thereby ensuring the computational efficiency and data security of the system 100.

[0038] Through the above system architecture, the embodiments of the present disclosure achieve behavior perception of the process of risk formation in a smart home scenario, achieve early and accurate risk alert effects, effectively improve the accuracy of risk recognition and response efficiency of household smart care for different individual family members, and solve the technical problem that the existing household smart care technologies are unable to recognize the process of risk evolution, making it difficult to achieve proactive prevention.

[0039] Exemplary Methods

[0040] FIG. 2 is a schematic flowchart of a method for constructing a behavior trend

model provided by an exemplary embodiment of the present disclosure. The present embodiment may be applied to a server. As shown in FIG. 2, the method may include the following steps.

[0041] Step 201: Performing association processing on behavior data sets of a plurality of users to obtain standard behavior data subsets corresponding to the users.

[0042] In some embodiments, in a smart home environment, the users may include family members who reside for a long term and temporary visitors who temporarily enter the residence for activities. As an optional implementation, family members and temporary visitors (e.g., maintenance workers, relatives, and friends) may be distinguished according to facial features of the users collected by a smart camera in combination with a dwell duration, wherein the dwell duration may be customized. Behavior data are continuously collected and analyzed for family members, while behavior data collected for temporary visitors are not analyzed.

[0043] The behavior data set may be collected and acquired by the perception module and the terminal device. The behavior data set may include movement trajectory data and an action data set associated with the movement trajectory data. For example, the action data set may include behavior action data, dwell time data corresponding to the behavior action data, device interaction behavior data, and the like.

[0044] Data in the behavior data set is identity-matched with different users, and the matched data is subjected to unification processing to obtain the standard behavior data subsets. For example, the unification processing may refer to uniform correction of timestamp errors caused by clock deviations of different devices, so as to ensure that the collection times of the same behavior in the same scenario are consistent across different devices.

[0045] Step 202: Dividing the standard behavior data subsets into a plurality of behavior chains based on a preset behavior association rule, the behavior chains being used for combining behavior data in the standard behavior data subsets to form a complete behavior process.

[0046] In some embodiments, the preset behavior association rule refers to a logical criterion for determining the correlation between discrete behavior data, for example,

the behavior association rule may be a temporal sequence, spatial position adjacency, or a behavior logic.

[0047] For example, "getting up, then opening the door, and then to the bathroom" is determined to be a behavior of going to the toilet or washing up, based on the association of the action data according to a temporal sequence and/or spatial position adjacency.

[0048] In some embodiments, the behavior chains refer to an ordered data sequence, obtained after being concatenated according to the behavior association rule, which is capable of reflecting a complete and independent behavior process, wherein each behavior chain corresponds to a complete event, integrating originally isolated single-point behaviors into an analyzable, complete process.

[0049] For example, the manner of dividing the behavior chains may be as follows: firstly, all items of behavior data in the standard behavior data subsets are traversed; all single-point behaviors are preliminarily sorted according to collection timestamps, and then grouped and aggregated according to the spatial position adjacency and behavior logic; and finally, the current grouping is terminated when a behavior space jump exceeds a preset range or a time interval exceeds a threshold (for example, when the next behavior occurs only one hour after washing up is completed). The ordered behavior sequence concatenated within the current group is a single independent behavior chain. The above process is repeated until all items of behavior data have been divided into the corresponding behavior chains, thereby ultimately obtaining a plurality of behavior chains for the users.

[0050] For example, "getting up in the bedroom at 7:00, then walking to the bathroom at 7:02, and finally turning on the washbasin faucet at 7:03" is determined as a behavior chain of the user corresponding to morning washing.

[0051] Step 203: Determining a stability data set of the behavior chains based on a monitoring period.

[0052] In some embodiments, the monitoring period refers to a preset, continuous time interval used for statistically analyzing a user's behavior regularity, and is used for collecting sufficient behavior chain data to obtain user's stable behavior habits. The

monitoring period may be customized, for example, three months.

[0053] The stability data set is fluctuation data of each action of each behavior chain of the user, obtained through statistics within the entire monitoring period, and is used for reflecting a conventional change range of the corresponding behavior of the user. For example, the stability data set may include statistical features of the behavior chains such as an average occurrence time, a time fluctuation range, an average spatial dwell duration, a spatial distribution range, a weekly occurrence frequency, and a behavior sequence order deviation.

[0054] Exemplarily, taking the behavior chain of morning washing up as an example, the user generally gets up and washes up around 7 o'clock, with a fluctuation range between 6:40 and 7:20, and an average washing duration of 10 minutes, ranging from 8 to 12 minutes, and occurring 6 to 7 times per week. These statistically derived regularity ranges are stability data of this behavior chain. It can thus be understood that the aggregation of such data for all behavior chains constitutes the stability data set.

[0055] Step 204: Constructing a behavior trend model based on the stability data set.

[0056] In some embodiments, the statistical features of each behavior chain (including an average occurrence time, a time fluctuation threshold, a spatial distribution range, an average dwell duration, a periodic occurrence frequency, and a behavior sequence consistency rate) are organized into a multidimensional feature vector; the multidimensional feature vectors of all behavior chains of the user are then integrated to construct a behavior matrix exclusive to the user; and meanwhile, a deviation alert threshold is set for each feature dimension. Finally, the behavior matrix and the corresponding deviation threshold are integrated and stored as a callable model file, thereby ultimately obtaining the personalized behavior trend model for the user.

[0057] For example, taking the behavior chain of morning washing up as an example, the average occurrence time obtained through statistics is 7:05, the time fluctuation threshold is ±25 minutes, the spatial distribution range is defined as an entrance bathroom area, and the frequency threshold is at least 5 occurrences per week.

[0058] With the technical solutions provided by the embodiments of the present disclosure, only the data of family members may be analyzed, effectively avoiding

behaviors of unrelated persons from interfering with the accuracy of the model. Meanwhile, the problem of asynchronous data from a multi-source device is solved through unification processing, laying a precise and unified data foundation for subsequent analysis. On this basis, discrete single-point behaviors are aggregated into a complete behavior chain based on a behavior association rule based on time, space and logic, such that user activities are understood from the dimension of the behavior process, rather than by recognizing isolated individual actions. Further, by statistically analyzing a feature fluctuation range of each behavior chain over the monitoring period, the stability data set is obtained, from which a long-term behavior habit regularity unique to the corresponding user can be accurately extracted, ultimately constructing the personalized behavior trend model.

[0059] This solves the problem of an excessively high false alarm rate caused by the traditional general-purpose model being unable to adapt to different users' living habits, and also provides an accurate personalized comparison reference for subsequent real-time behavior deviation detection, thereby, on the whole, greatly improving the accuracy of behavior analysis and the response efficiency of risk alert in a household smart care scenario.

[0060] As shown in FIG. 3, on the basis of the embodiment shown in FIG. 2 above, step 201 may specifically include the following steps.

[0061] Step 2011: Acquiring feature information and behavior data sets of a plurality of users, the behavior data sets including movement trajectory data and an action data set associated with the movement trajectory data.

[0062] In some embodiments, the feature information refers to identifiable individual biological or appearance features used for distinguishing different users and completing identity matching, which may be directly collected by various types of perception devices of the smart home.

[0063] For example, the feature information may be facial features, gait features, height features, or clothing features. The feature information may be collected by a smart camera.

[0064] In some embodiments, the behavior data set may include movement trajectory

data and an action data set associated with the movement trajectory data. For example, the action data set may include behavior action data, dwell time data corresponding to the behavior action data, and device interaction behavior data, etc.

[0065] For example, the behavior action data refers to perception data of specific action types and parameters of a user. Specifically, recognition results of specific action types such as getting up, walking, sitting down, falling, opening/closing a door, and picking up an object, as well as parameters such as amplitudes and forces of the actions, are generally obtained by extracting human skeletal point action features via a millimeter-wave radar and recognizing visual action features via a smart camera, followed by algorithmic classification.

[0066] The dwell time data refers to statistical data of a duration for which a user continuously stays in a specific spatial area, to be specific, duration data such as the user staying in the bedroom for 10 minutes after getting up, or staying in the bathroom for 8 minutes while washing up, which is generally obtained by extracting start and end timestamps at which user's position coordinates in the movement trajectory data do not exceed a threshold change, and calculating a difference.

[0067] The device interaction behavior data refers to recorded data of a user's interaction behavior with a terminal device of the smart home, to be specific, records of operations such as the user locking/unlocking a smart door lock, adjusting the volume of a smart speaker, opening a refrigerator door, or triggering a smart toilet sensor, which are generally acquired directly by the corresponding smart device reporting interaction events and timestamps.

[0068] Step 2012: Determining identity information of the users based on the feature information.

[0069] In some embodiments, a family member identity feature library may be pre-stored in the smart home system, and may specifically include basic information such as facial features, gait features, and height features.

[0070] For example, any one of the facial features, gait features, height features, or clothing features may be individually selected and compared with the pre-stored identity feature library to complete determination of user's identity information; or two or more

features may be selected for weighted fusion to obtain a comprehensive matching score, based on which the user's identity information is determined, wherein specific fusion weights may be adaptively adjusted according to the collection accuracy of different devices.

[0071] For example, when the clarity of the facial features collected by a camera is relatively high, a matching weight of the facial features may be appropriately increased; and when poor lighting conditions reduce the extraction accuracy of the facial features, a matching weight of the gait features collected by a millimeter-wave radar may correspondingly be increased, so as to ensure the accuracy of identity recognition in different scenarios.

[0072] Exemplarily, when indoor lighting conditions of the home are sufficient, a smart camera in an entrance area may clearly collect facial features of an incoming person; the extracted facial features are compared with the pre-stored identity feature library to obtain a matching score of 94% for the father, Mr. Zhang, which exceeds a preset single-feature identity determination threshold of 88%. Therefore, the identity of this person is determined solely based on the facial feature as being the head of household, Mr. Zhang.

[0073] When lighting in the entrance area is insufficient at night, the smart camera cannot clearly extract facial features, but the millimeter-wave radar collects a gait feature of an incoming person, and the smart camera can still extract a stable height contour feature. The gait feature and the height feature are respectively compared with the feature library to obtain a matching score of 87% for the gait feature corresponding to the mother, Ms. Liu, and a matching score of 91% for the height feature corresponding to the mother, Ms. Liu; a preset gait weight is 0.4 and a height weight is 0.6; and the calculated comprehensive matching score is $87\times0.4+91\times0.6=89.4\%$, which exceeds a preset comprehensive determination threshold of 85%. Therefore, the identity of this person is determined based on the fusion of the two features as being the mother, Ms. Liu.

[0074] Step 2013: Performing time alignment and semantic alignment on the movement trajectory data and the action data set to obtain a standard behavior data set.

[0075] In some embodiments, the behavior action data, dwell time data, and device interaction behavior data, which are attributed to the corresponding user, are split out, sorted according to unified reference timestamps corrected for each item of data, and sequentially matched and bound to user's movement trajectory points in the same time window; and meanwhile, heterogeneous behavior descriptions output by different terminal devices are uniformly mapped and converted into preset standard semantic labels, so as to obtain standard behavior data sets that are time-synchronized and uniformly described.

[0076] For example, the millimeter-wave radar collects an original action code, Radar_Motion, with a reference time of 18:15:22, corresponding to an original behavior description of "continuous displacement movement of a human skeleton detected". The smart camera collects an original trajectory code, Camera_Walk, for the same time range, corresponding to an original trajectory description of "a continuous walking visual trajectory of the user recognized".

[0077] First, original timestamps output by two types of devices are uniformly corrected to a reference time of a smart home hub clock. After confirming that time windows of the two types of data completely coincide, they are uniformly mapped to a standard behavior semantic label, Walk_Action, according to a preset mapping rule. Then, time-matched millimeter-wave radar action features and movement trajectory points of the smart camera are bound to the standard semantic label, Walk_Action, ultimately obtaining a single item of standard behavior data: "at 18:15, the user exhibits a walking behavior in the dining area". It can thus be seen that all such matched and mapped homogeneous data are aggregated to constitute the standard behavior data set for the corresponding user.

[0078] Step 2014: Associating the identity information with the standard behavior data set, to obtain the standard behavior data subsets corresponding to the users.

[0079] In some embodiments, each item of data in the aligned standard behavior data set is associated and bound with the determined corresponding user identity information. After a standard behavior data subset exclusive to a single user is obtained by splitting according to the identity information, behavior data within the subset is divided and

aggregated based on a preset behavior association rule, ultimately obtaining a plurality of independent behavior chains belonging solely to the corresponding user.

[0080] With the above embodiment, from feature collection, identity determination, and multi-source data alignment to identity-association splitting, noise filtering and standardization processing are completed at a data source level, and the problems of asynchronous time and inconsistent expression of data from multi-source heterogeneous devices are solved by means of time alignment and semantic alignment, such that behavior data dispersed across different devices can be accurately matched and integrated into the standardized data set. Ultimately, a standard behavior data subset exclusive to a single user is obtained by means of identity-associated splitting, which not only ensures the purity and accuracy of subsequent behavior analysis data, but also provides standardized foundational data support for the construction of a personalized behavior trend model, thereby reducing errors in subsequent behavior chain division and trend modeling from the source, and improving the reliability and accuracy of the overall behavior analysis process.

[0081] As shown in FIG. 4, on the basis of the embodiment shown in FIG. 3 above, step 2013 may further specifically include the following steps.

[0082] Step 2015: Classifying, based on the same time axis, each item of behavior data in the action data sets from different collection terminals, to obtain a plurality of time-aligned data sets.

[0083] In some embodiments, after unified correction of timestamps of all behavior data has been completed, all data is projected onto the same time axis referenced to the smart home hub clock, and the action data sets are classified according to a device type of a terminal device.

[0084] First, all behavior action data from the millimeter-wave radar on the time axis are extracted and aggregated to obtain a first type of time-aligned data set, including all skeletal action feature data at corresponding timestamps. Then, all action recognition data from the smart camera are extracted and aggregated to obtain a second type of time-aligned data set, including all visual action recognition data at corresponding timestamps. Finally, device interaction data reported by all smart terminals (e.g., a smart

sofa, a smart door lock, and a smart refrigerator) connected to the smart home system are extracted and aggregated to obtain a third type of time-aligned data set, including all device interaction event data at corresponding timestamps. All three types of data sets are sorted based on the same reference time axis, such that data collected by different terminals at the same time node can be directly matched with each other, completing preliminary alignment and classification in a time dimension.

[0085] For example, taking collected data from 18:10 to 18:20 on a given day as an example, five sets of skeletal action data collected by the millimeter-wave radar, three sets of visual action data collected by the smart camera, and two sets of device interaction data each reported by a smart sofa and a smart refrigerator, within this time interval, are classified according to the same time axis into three time-aligned data sets, namely a millimeter-wave radar category, a smart camera category, and a smart terminal interaction category. The data within each data set is sorted in order of reference timestamps, and may be directly used for subsequent semantic alignment matching.

[0086] Step 2016: Performing semantic unification on each item of behavior data from different collection terminals in the time-aligned data sets, to obtain the standard behavior data set.

[0087] For example, in the time-aligned data sets of the millimeter-wave radar, the original description of data at 18:15 is "continuous displacement of a human skeleton detected", which is uniformly converted to a standard label "walking" according to a mapping rule; in the time-aligned data sets of the smart camera, the original description of data at the same time node is "a continuous movement trajectory of the user recognized", which is likewise mapped to a standard label "walking"; and in the interaction time-aligned data sets of the smart terminal, the original description reported by the smart refrigerator at 18:18 is "refrigerator door opening/closing triggered", which is mapped to a standard label "opening/closing refrigerator door".

[0088] With the above embodiment, by first classifying according to a device type based on a unified time axis to obtain the time-aligned data sets, and then performing semantic unification on different behavior descriptions output by different terminals,

multi-source data corresponding to the same behavior can be quickly matched and bound from a time dimension, thereby avoiding matching errors caused by disordered timing of different device data, while also solving, from a semantic level, the problem of inconsistent expression of the same behavior by different collection terminals, and eliminating a semantic barrier between multi-source heterogeneous data. Therefore, scattered and independent multi-device data can be accurately fused into usable standardized data. Compared with a direct alignment processing method, this further reduces matching errors and improves alignment efficiency, while also providing a standardized data foundation of higher accuracy and better consistency for subsequent identity association and behavior modeling, thereby ensuring, on the whole, the data reliability of the entire behavior trend model construction process.

[0089] As shown in FIG. 5, on the basis of the embodiment shown in FIG. 2 above, step 202 may specifically include the following steps.

[0090] Step 2021: Classifying adjacent action behavior data into the same behavior chain, based on a time continuity sub-rule and a behavior logic sub-rule in the behavior association rule.

[0091] In some embodiments, the time continuity sub-rule refers to a basic time determination criterion, in behavior association division, for determining whether two adjacent actions belong to the same complete behavior process. The behavior logic sub-rule refers to a logical determination criterion, based on a user's daily behavior habit logic, for determining whether adjacent actions have a causal sequential relationship.

[0092] Further, as shown in FIG. 6, step 2021 may further specifically include the following steps.

[0093] Step 2024: In response to the time continuity sub-rule, determining that a difference between occurrence times of the adjacent action behavior data is less than a preset threshold, and classifying the adjacent action behavior data into the same behavior chain.

[0094] In some embodiments, a maximum allowable time interval threshold may be preset; if a timestamp difference between two the adjacent action behavior data is less

than the threshold, it is determined that the two adjacent items satisfy a time continuity and belong to the same behavior process; and if the difference is greater than the threshold, it is determined that the two adjacent items belong to different behavior processes.

[0095] Exemplarily, reference timestamps of adjacent actions are, in sequence: "getting up" at 7:00, "walking out of the bedroom door" at 7:02, "entering the bathroom" at 7:03, and "turning on the washbasin faucet" at 7:05.

[0096] A time interval between 7:02 and 7:00 is 2 minutes, which is less than a preset time continuity threshold of 10 minutes, satisfying the time continuity sub-rule; and meanwhile, going from getting up to walking out of the bedroom conforms to a daily behavior logic of going out of the bedroom after waking up in the morning, satisfying the behavior logic sub-rule. Therefore, the two actions are divided into the same behavior chain.

[0097] After 7:05, the next action "opening the refrigerator door in the living room" has a timestamp of 8:10, with an interval of 65 minutes from 7:05, which is far greater than the preset time continuity threshold of 10 minutes, and does not satisfy the time continuity sub-rule. Therefore, the division of the current behavior chain is terminated, and the above four adjacent actions are ultimately determined to be a complete "morning washing up" behavior chain.

[0098] Step 2025: In response to the behavior logic sub-rule, determining that the adjacent action behavior data conform to a preset logical relationship, and classifying the adjacent action behavior data into the same behavior chain.

[0099] In some embodiments, on the basis of step 2024, the behavior logic sub-rule is simultaneously used to verify whether actions that are time-continuous truly belong to the same complete behavior, so as to avoid mistakenly dividing actions that are close in time but logically unrelated into the same behavior chain.

[00100] Exemplarily, a time interval between 7:03 and 7:02 is 1 minute, which is less than a threshold of 10 minutes, satisfying a time continuity; and going from walking out of the bedroom to entering the bathroom also conforms to a behavior logic of morning washing up, satisfying the behavior logic sub-rule, and is thus continuously divided into

the same behavior chain. Similarly, a time interval between 7:05 and 7:03 is 2 minutes, satisfying a time continuity; and turning on the washbasin faucet following entry into the bathroom conforms to a logic, and is thus also divided into the same behavior chain.

[00101] Step 2022: Associating occurrence spaces of the adjacent action behavior data based on a spatial continuity sub-rule in the behavior association rule, to determine the same as a continuous path of the same behavior chain.

[00102] In some embodiments, the spatial continuity sub-rule refers to a determination criterion, in behavior association division, for verifying the correlation between adjacent actions based on a spatial positional relationship at which the actions occur.

[00103] For example, a maximum distance threshold between occurrence positions of two adjacent actions may be preset; and if a Euclidean distance between the occurrence spaces of the adjacent actions is less than a threshold, it is determined that the two actions satisfy a spatial continuity and belong to a continuous path of the same behavior chain. If the distance is greater than the threshold, it is determined that the two actions are spatially discontinuous and belong to different behavior processes. This rule further verifies, from a spatial dimension, the rationality of the behavior chain division, and avoids forcibly dividing actions that satisfy time and logic criteria but have an extremely large spatial span into the same behavior chain.

[00104] Exemplarily, the preset maximum distance threshold for the spatial continuity is 3 meters, that is, if a spatial distance between the occurrence positions of adjacent actions is less than 3 meters, the spatial continuity is satisfied.

[00105] Occurrence space coordinates of a first action "getting up" is a bedroom bed area (12, 5), and occurrence space coordinates of a second action "walking out of the bedroom door" is a bedroom doorway (15, 6). A spatial distance between the two points is calculated to be approximately 3.16 meters, having a deviation within a preset allowable range, satisfying the spatial continuity sub-rule. Therefore, the two actions are confirmed to belong to a continuous path of the same behavior chain.

[00106] Occurrence space coordinates of a third action "entering the bathroom" is a bathroom doorway (17, 6), which has a spatial distance of approximately 2 meters from the previous action "walking out of the bedroom door", which is less than a threshold of

3 meters, satisfying the spatial continuity, and is thus continuously divided into the continuous path of the same behavior chain.

[00107] Occurrence space coordinates of a fourth action "turning on the washbasin faucet" is a bathroom washbasin (18, 7), which has a spatial distance of approximately 1.41 meters from "entering the bathroom", satisfying the spatial continuity, and is likewise divided into the continuous path of the current behavior chain.

[00108] Occurrence space coordinates of the subsequent next action to be divided, "opening the refrigerator door in the living room", is a living room refrigerator area (8, 10), which has a spatial distance of approximately 10.44 meters from "turning on the washbasin faucet", which is far greater than a preset threshold of 3 meters and does not satisfy the spatial continuity sub-rule. Therefore, the determination to terminate the division of the current behavior chain is further verified from the spatial dimension.

[00109] Step 2023: Dividing the standard behavior data subsets into a plurality of behavior chains based on the continuous path of the same behavior chain.

[00110] In some embodiments, firstly, all behavior data in the standard behavior data subsets are sorted in ascending order according to unified reference timestamps, to obtain a behavior sequence to be divided. Then, starting from the first item of behavior data in the sequence, each subsequent adjacent item of behavior data is traversed in turn, sequentially matched against the time continuity sub-rule, the behavior logic sub-rule, and the spatial continuity sub-rule. When adjacent behaviors simultaneously satisfy all three rules, they are divided into the continuous path of the same behavior chain currently being constructed.

[00111] When a certain adjacent behavior that fails to satisfy any one of the rules is traversed, construction of the current behavior chain is terminated, and the continuous path that has already been aggregated is saved as one complete behavior chain. Then, a next new behavior chain is re-constructed starting from the behavior data that does not satisfy the rule. The above traversal determination process is repeated until all items of behavior data in the behavior sequence have been divided into the corresponding behavior chains, and ultimately, the complete standard behavior data subset is split into a plurality of independent behavior chains.

[00112] Exemplarily, starting sequentially from the first item "7:00 - getting up - bedroom bed", the determination proceeds in sequence. The first four items of behaviors (getting up, walking out of the bedroom, entering the bathroom, and turning on the faucet) all simultaneously satisfy all three rules, and are aggregated into the continuous path of the current behavior chain. Upon reaching the fifth item of behavior "8:10 - opening the refrigerator door - living room", the time continuity and spatial continuity rules are not satisfied, and the division is therefore terminated. The continuous path of the first four items is saved as the first complete behavior chain "morning washing up".

[00113] Construction of a new behavior chain is then restarted from the fifth item of behavior. Subsequent adjacent behaviors that satisfy the rules continue to be aggregated, while those that do not are cut and divided. Ultimately, twelve items of behavior data are split into four independent behavior chains, namely "morning washing up", "breakfast preparation", "working from home" and "evening washing up", completing the entire division process.

[00114] With the above embodiment, a preliminary behavior division is completed via the time continuity rule; the behavior logic rule then excludes erroneous aggregation of behaviors that are close in time but logically unrelated; and the spatial continuity rule further excludes erroneous divisions in which the time and logic criteria are satisfied but the spatial span is unreasonable, thereby effectively solving the problems of large errors and high error rates in behavior chain division using a single rule, and improving the accuracy and reasonableness of behavior chain division. Therefore, each behavior chain obtained through division corresponds to a complete, independent user behavior process, which is capable of accurately restoring user's true household behavior habits, thereby providing clearly structured and highly accurate foundational data support for subsequent behavior trend modeling, and thus improving the reliability of subsequent user behavior analysis and abnormality determination.

[00115] As shown in FIG. 7, on the basis of the embodiment shown in FIG. 5 above, the method may further specifically include the following step.

[00116] Step 2026: Classifying the plurality of behavior chains based on a preset behavior chain classification rule, to determine a daily routine behavior chain, a

high-frequency behavior chain, and an abnormal behavior chain.

[00117] In some embodiments, the behavior chain classification rule refers to a graded classification rule formulated based on an occurrence frequency and occurrence time/space regularity of the behavior chains.

[00118] For example, the number of occurrences of each behavior chain within the last 30 days, as well as a time window deviation and a spatial position deviation of each occurrence, may first be statistically counted. If a behavior chain occurs ≥5 times per week, with each occurrence deviating no more than 1 hour from a reference habitual time, and with a spatial position being completely fixed, it is classified as the daily routine behavior chain.

[00119] If a behavior chain occurs ≥8 times per month but fewer than 5 times per week, or the occurrence time deviation exceeds 1 hour while the spatial position is fixed, it is classified as the high-frequency behavior chain.

[00120] If a behavior chain occurs ≤1 time within the last 30 days, or the occurrence time or space deviation far exceeds a user's daily habitual interval (a time deviation exceeding 3 hours, or a spatial position deviating more than 5 meters from a daily path), it is classified as the abnormal behavior chain.

[00121] Exemplarily, morning washing up (around 7 o'clock, bedroom-bathroom) occurs 26 times within the last 30 days, averaging 6.5 times per week, with each occurrence time concentrated between 6:40 and 7:40, with a deviation not exceeding 1 hour, and with a spatial path fixed as bedroom bed to bathroom washbasin, conforming to determination criteria for the daily routine behavior chain, and is therefore classified as the daily routine behavior chain.

[00122] Watching TV in the living room (sofa area, evening) occurs 12 times within the last 30 days, averaging 3 times per week, with each occurrence time concentrated between 19:00 and 21:00, with a deviation of approximately 1.5 hours, and with a spatial position fixed at the sofa in the living room, conforming to determination criteria for the high-frequency behavior chain, and is therefore classified as the high-frequency behavior chain.

[00123] A nighttime fall (bathroom area, 2 a.m.) occurs only once within the last 30 days,

in which a user has no daily behavior records of remaining in the bathroom at 2 a.m., and both the occurrence time and behavior type deviate from a daily habitual interval, conforming to determination criteria for the abnormal behavior chain, and is therefore classified as the abnormal behavior chain.

[00124] With the above embodiment, by hierarchically classifying the behavior chains in combination with the occurrence frequency and spatiotemporal regularity, user's most stable and representative daily routine behaviors can be screened from disorderly user behavior data, while behaviors that are frequent for the user but have weaker regularity can be distinguished, and abnormal behaviors that deviate from user's daily habits can be quickly recognized to provide a data foundation for subsequent targeted modeling and analysis of different types of behaviors, which avoids the waste of resources caused by undifferentiated modeling, and allows abnormal behaviors to be more quickly and accurately located, thereby improving the efficiency and accuracy of subsequent behavior analysis and abnormality warning.

[00125] As shown in FIG. 8, on the basis of the embodiment shown in FIG. 2 above, step 203 may specifically include the following steps.

[00126] Step 2031: Acquiring, based on the monitoring period, a plurality of items of time data and a plurality of items of continuous path data of the behavior chain, as well as an occurrence frequency within a time data period.

[00127] In some embodiments, a natural month (30 days) is used as a preset monitoring period, over which target behavior chains that have already been classified are traversed.

[00128] For example, reference start timestamps recorded in each target behavior chain are extracted and aggregated to obtain a plurality of time data sets corresponding to the behavior chains. Occurrence space coordinate sequences of various actions recorded in each target behavior chain are extracted, and organized and aggregated to obtain a plurality of continuous path data sets corresponding to this behavior chain. A total number of occurrences of this behavior chain within the entire monitoring period is directly counted, and the counted total number of occurrences is used as the occurrence frequency of this behavior chain within the monitoring period.

[00129] Exemplarily, the monitoring period is set as May 1 to May 30, 2026, and the target behavior chain is a "morning washing up" behavior chain that has already been classified for the user. All behavior chain items marked as "morning washing up" within the entire monitoring period are traversed, and start timestamps recorded for each item (e.g., 7:02 on May 1, 6:58 on May 2, and so on) are extracted, and aggregated to obtain 26 items of time data for this behavior chain. A spatial coordinate sequence recorded for each item (all being "bedroom bed (12,5) - bedroom doorway (15,6) - bathroom doorway (17,6) - washbasin (18,7)") is extracted, and aggregated to obtain 26 sets of continuous path data. It is finally counted that this behavior chain occurs 26 times in total during the 30-day monitoring period, that is, the occurrence frequency is 26 occurrences per monitoring period, completing the acquisition of the three types of data.

[00130] Step 2032: Determining time regularity data of the behavior chain based on the plurality of items of time data and a preset time deviation threshold.

[00131] In some embodiments, the distribution features of all extracted time data are statistically counted, and combined with the preset deviation threshold for regularity verification, to derive the time regularity data of the behavior chains.

[00132] For example, firstly, all start time data of each behavior chain are converted into a normalized number of minutes within the current day, and an average of all normalized times is calculated as a reference habitual time of this behavior chain. Then, an absolute deviation between each actual occurrence time and the reference habitual time is calculated, and a proportion of the number of occurrences with a deviation within a preset time deviation threshold range relative to the total number of occurrences is statistically counted. If the proportion exceeds a preset qualifying proportion threshold, the reference habitual time and the deviation range are organized as the time regularity data of this behavior chain; and if the proportion is below the qualifying proportion threshold, this behavior chain is marked as having no stable time regularity.

[00133] Exemplarily, the target behavior chain "morning washing up" has a total of 26 items of time data, and are all normalized to a number of minutes within the current day, respectively 422 (7:02), 418 (6:58), and so on. An average of all times is calculated to be approximately 420 minutes, that is, a reference habitual time is 7:00. A time deviation

threshold is 60 minutes. After statistic counting, 25 of the 26 items of time data have a deviation within a range of 60 minutes, with a proportion of approximately 96.1%, which exceeds the preset qualifying proportion threshold of 85%. Therefore, the time regularity data of this behavior chain is determined as: a reference habitual time of 7:00, with an allowable deviation range of ±60 minutes.

[00134] If, of the 12 items of time data for the target behavior chain "watching TV in the living room", only 6 have a deviation within a preset threshold of 120 minutes, with a proportion of 50%, which is below the qualifying proportion of 85%, and this behavior chain is marked as having no stable time regularity.

[00135] Step 2033: Determining spatial regularity data of the user corresponding to the behavior chain based on the time regularity data of the behavior chain and the plurality of items of continuous path data.

[00136] In some embodiments, statistical aggregation is performed on all continuous path data in combination with the time regularity data of the behavior chain, to obtain the spatial regularity data.

[00137] For example, firstly, whether this behavior chain has been determined to have stable time regularity data is determined; and if the stable time regularity data exists, the spatial coordinates corresponding to each action in all continuous path data of this behavior chain are extracted. Average coordinates of each action's position are respectively calculated as a reference spatial position. A proportion of a deviation between an actual position of each action and the reference position is then statistically counted. After it is confirmed that the proportions of the deviations of all actions satisfies a preset spatial deviation requirement, the sequentially arranged reference spatial coordinate sequences of the actions are organized as the spatial regularity data of this behavior chain.

[00138] If this behavior chain has no stable time regularity, spatial frequency statistics are directly performed on all continuous paths, and only a spatial path whose occurrence frequency exceeds a preset proportion is marked as the spatial regularity data of this behavior chain; and if no path reaches the frequency threshold, it is marked as having no stable spatial regularity.

[00139] Exemplarily, a target behavior chain "morning washing up" has been determined to have stable time regularity, and among its 26 sets of continuous path data, each set includes spatial coordinates of 4 actions. Average coordinates of the four actions are respectively calculated to obtain a reference position: "getting up" corresponds to a bedroom bed area (12, 5), "walking out of the bedroom door" corresponds to a bedroom doorway (15, 6), "entering the bathroom" corresponds to a bathroom doorway (17, 6), and "turning on the washbasin faucet" corresponds to a bathroom washbasin (18, 7). The deviations between all actual positions and the reference position are statistically counted, and 96% of the deviations are within a preset 0.5-meter deviation threshold, which satisfies a requirement. Therefore, this coordinate sequence is organized as the spatial regularity data for "morning washing up". If a certain behavior chain has no stable time regularity, and among 12 sets of continuous path data, 8 sets have a consistent spatial path, with a proportion exceeding a preset frequency threshold of 60%. Then, this consistent path is marked as the spatial regularity data; and if only 3 sets of paths are consistent, it is marked as having no stable spatial regularity.

[00140] Step 2034: Determining a plurality of occurrence frequencies of the behavior chain based on the plurality of items of time data and the occurrence frequency within the time data period, and determining behavior regularity data based on the plurality of occurrence frequencies.

[00141] The stability data set includes the time regularity data, the spatial regularity data, and the behavior regularity data.

[00142] In some embodiments, a plurality of sets of occurrence frequencies may first be obtained by splitting statistics in a time dimension, and the stability may then be determined by means of frequency fluctuation features, and ultimately, the behavior regularity data is determined.

[00143] For example, firstly, based on all extracted time data, the entire monitoring period is split into a plurality of continuous sub-periods according to a fixed time granularity (such as a natural week), and each sub-period is traversed to count the number of occurrences of the target behavior chain within that sub-period, obtaining a

plurality of sub-period occurrence frequencies corresponding to the plurality of sub-periods.

[00144] A discrete variance of all sub-period occurrence frequencies is then calculated, and the variance is compared with a preset frequency fluctuation threshold. If the variance is less than the threshold, it indicates that the behavior occurrence frequency is stable, and an average occurrence frequency over the entire monitoring period is used as the behavior regularity data of this behavior chain. If the variance is greater than or equal to the threshold, it indicates that the frequency fluctuation is large with no stable regularity, and this behavior chain is marked as having no stable behavior regularity. The determined behavior regularity data is finally integrated with the previously obtained time regularity data and spatial regularity data, together constituting the stability data set of the corresponding behavior chain.

[00145] Exemplarily, the target behavior chain "morning washing up" has a total monitoring period of 30 days. Based on 26 recorded items of time data, the entire period is split into 4 natural-week sub-periods, and occurrence frequencies of the four sub-periods are counted to be 6, 7, 7, and 6 times per week, respectively. A variance of the four frequencies is calculated to be approximately 0.25, which is far less than a preset fluctuation threshold of 1. Therefore, the behavior regularity data of this behavior chain is determined to be an average of 6.5 occurrences per week. The stability data set for "morning washing up" is ultimately integrated as: time regularity data (a reference of 7:00, and a deviation of ±60 minutes), spatial regularity data (a fixed coordinate sequence of bedroom bed - bedroom doorway - bathroom doorway - washbasin), and behavior regularity data (an average of 6.5 occurrences per week).

[00146] Based on the above embodiment, stable time regularity is first extracted through normalized statistics combined with deviation proportion verification. Spatial regularity is then extracted by adapting different statistical strategies in combination with the time stability. Finally, regularity features of the occurrence frequencies are determined by means of sub-period variance determination, which not only accommodates the regularity extraction needs of behavior chains with different degrees of stability, avoiding forced fitting of behaviors with no stable regularity, but is also able

to accurately extract user's true, stable behavior habit features, such that the ultimately generated stability data set can comprehensively and accurately reflect the inherent regularity of the user's daily behaviors, and significantly improving the accuracy of subsequent behavior abnormality determination compared with single-dimensional regularity extraction.

[00147] As shown in FIG. 9, on the basis of the embodiment shown in FIG. 2 above, step 204 may specifically include the following steps.

[00148] Step 2041: Analyzing a fluctuation condition of the behavior chain according to the stability data set, to determine a stability degree of the behavior chain.

[00149] In some embodiments, based on the regularity features in three dimensions of time, space, and behavior frequency contained in the stability data set, a fluctuation score is respectively calculated for each dimension and then weighted and aggregated, and the stability degree of the behavior chain is ultimately determined based on a total score.

[00150] For example, firstly, for dimensions having explicit regularity data, an average deviation between an actual occurrence value and a regularity value is calculated; and for dimensions having no explicit regularity data, a fixed fluctuation score value is directly marked. Then, the fluctuation score values of each dimension are then weighted and summed according to preset weights to obtain a total fluctuation score. Finally, the total fluctuation score is compared with a preset stability grade threshold, wherein a total fluctuation score below a first threshold is determined as high stability, a score between the first threshold and a second threshold is determined as medium stability, and a score above the second threshold is determined as low stability, thereby completing the determination of the stability degree of the behavior chain.

[00151] In some embodiments, the behavior deviation in each behavior chain may be calculated, and a variance of the behavior chain may be calculated based on the behavior deviation, according to the following formula:

[00152] $$BehaviorVariance = \frac{1}{N}\sum_{i=1}^{N}(B_i - \overline{B})^2$$

[00153] wherein,

[00154] B_i is a single behavior;

[00155] $\overline{B}$ is an average behavior; and

[00156] $BehaviorVariance$ is the variance of the behavior chain.

[00157] Exemplarily, the stability data set of the target behavior chain "morning washing up" is: time regularity (a reference of 7:00, and a deviation of ±60 minutes), spatial regularity (a fixed coordinate sequence, an allowable deviation of 0.5 meters), and frequency regularity (an average of 6.5 occurrences per week). A calculated actual average time deviation is 18 minutes, an average spatial deviation is 0.2 meters, and a weekly frequency variance is 0.25, which, after conversion into standardized fluctuation scores, are respectively 0.18, 0.2, and 0.2. The weighted summation gives a total fluctuation score of 0.194, which is below a first threshold of 0.3. Therefore, this behavior chain is determined to have a high stability degree.

[00158] The behavior chain "watching TV in the living room" has no stable time regularity, with a time dimension fluctuation score recorded as 0.8, a spatial dimension average deviation of 0.3 recorded as 0.3, and a frequency variance of 1.2 recorded as 0.6; and a weighted total fluctuation score is 0.59, which is between a first threshold of 0.3 and a second threshold of 0.7. Therefore, it is determined to have a medium stability degree.

[00159] The abnormal behavior chain "nighttime fall" occurs only once, with no stable regularity in any of the three dimensions, and a total fluctuation score of 0.9, which is above a second threshold of 0.7, and is thus determined to have a low stability degree.

[00160] Step 2042: Obtaining the behavior trend model based on the stability data set, in a case where the stability degree of the behavior chain conforms to a preset range.

[00161] In some embodiments, firstly, a qualifying threshold for the stability degree is preset, and only behavior chains determined to have a high or medium stability degree are included within a modeling scope. Then, the time regularity data, spatial regularity data, and behavior regularity data in the stability data set of the target behavior chain are used as feature parameters, and the behavior trend model of the behavior chain is constructed by means of fitting according to a structure of "a reference value and an allowable fluctuation range". The model may output a probability range of the behavior chain occurring within any future time window, as well as the expected occurrence time,

spatial path, and occurrence frequency. After the modeling is completed, a consistency verification is performed on the model, and after it is confirmed that a deviation between output results and historical statistical data is within an allowable range, a usable behavior trend model is thereby obtained.

[00162] Exemplarily, the "morning washing up" behavior chain is determined to have a high stability degree, conforming to the preset qualifying range. Three types of parameters of its stability data set are extracted, namely time regularity parameters (a reference occurrence time of 7:00, with an allowable deviation of ±60 minutes), spatial regularity parameters (a fixed path coordinate sequence, with a single action allowable deviation of 0.5 meters), and behavior regularity parameters (an average of 6.5 occurrences per week, with an allowable weekly frequency fluctuation range of ±1 occurrence). The three types of parameters are fitted to construct a behavior trend model for "morning washing up", which may output an expected number of occurrences of the behavior chain in the coming week of 6-7 times, with each expected occurrence time concentrated between 6:00 and 8:00, and an expected path being a fixed bedroom-to-bathroom sequence. After verification, the output deviation meets requirements, and the usable behavior trend model for the behavior chain is ultimately obtained.

[00163] Based on the above embodiment, through a process of first determining the stability degree of the behavior chain based on multidimensional weighted fluctuations, and then modeling only behavior chains that satisfy preset stability requirements, the comprehensiveness of the stability degree determination is ensured from a dimensional perspective, with the stability of the behavior being accurately quantified in combination with time, space, and frequency, while also avoiding interferences to the modeling process from behavior chains with no regular data by filtering out low-stability behavior chains, thereby reducing the resource consumption of ineffective modeling. Meanwhile, by fitting the model based on the structure of "a reference value and an allowable fluctuation range", inherent regularity features of the user's behaviors are retained, while reasonable room is also reserved for normal fluctuations in the user's behaviors, thereby avoiding excessive misjudgment of normal fluctuations, such that the ultimately

obtained behavior trend model can more closely match user's true behavior habits, and output trend prediction results are both accurate and reasonable, providing a reliable basis for subsequent abnormal behavior detection, and thereby improving, on the whole, the accuracy and operational efficiency of a user household behavior analysis system.

[00164] FIG. 10 is a schematic flowchart of a behavior deviation detection method provided by an exemplary embodiment of the present disclosure. The present embodiment may be applied to an electronic device and a server. As shown in FIG. 2, the method may include the following steps.

[00165] Step S301: Acquiring a behavior data set of a user.

[00166] In some embodiments, real-time collection is performed by a perception module and a terminal device, and the collected raw data is preprocessed and then aggregated for storage.

[00167] For example, via a plurality of perception terminals deployed in a user's household environment, such as an infrared sensor, a human perception device, a spatial positioning apparatus, and a linkage collection module of a smart home appliance, raw data such as timestamps, spatial position coordinates, and behavior type labels corresponding to all of the user's action behaviors are collected in real time. All collected raw data is cleaned and aligned according to a uniform format, and, after removing invalid data resulting from duplicate collection or device false triggering, is uniformly stored in a user-exclusive behavior database on the server, and integrated to obtain the user's complete behavior data set, from which corresponding data can subsequently be directly retrieved for analysis and processing.

[00168] Step S302: Determining the behavior data set as a plurality of behavior chains based on a behavior trend model.

[00169] In some embodiments, the division is completed by reusing the aforementioned three-tier association rules for behavior chain division, in combination with the regularity feature division of the behavior trend model.

[00170] For example, firstly, the newly acquired behavior data set of the user is sorted in ascending order by timestamps, and a time continuity sub-rule, a behavior logic sub-rule, and a spatial continuity sub-rule are reused to perform a preliminary division,

to obtain candidate behavior chains. Time and space features of each candidate behavior chain are then matched against a regularity reference recorded in the behavior trend model. If the candidate behavior chain conforms to a fluctuation range of an existing regularity, it is directly classified as a behavior chain corresponding to the existing model; and if it does not conform to the regularity range of any existing model, it is marked as a newly added, independent behavior chain to be analyzed. This ultimately completes the division of all behavior data, obtaining a plurality of behavior chains corresponding to the new behavior data set.

[00171] Step S303: Calculating a deviation degree of each behavior chain, and outputting warning information in a case where the deviation degree is greater than a preset threshold.

[00172] In some embodiments, based on regularity parameters of the behavior trend model, deviation values of the behavior chain in four dimensions, namely time, space, frequency, and the behavior chain itself, are respectively calculated. Deviation values in the four dimensions are weighted and aggregated to obtain a total deviation degree of this behavior chain, which is then compared with a preset threshold to trigger a warning.

[00173] For example, firstly, the actual occurrence time, actual spatial path, actual occurrence frequency, and actual behavior sequence (that is, the composition and order of the actions) of the behavior chain to be detected currently are extracted, and respectively compared with the regularity reference in the corresponding behavior trend model. A proportion of an absolute deviation between an actual value and a reference value in each dimension relative to an allowable fluctuation range is calculated to obtain a single-dimension deviation value. The deviation values in the four dimensions are then weighted and summed according to preset weights (for example, time accounting for 20%, space accounting for 20%, frequency accounting for 30%, and behavior sequence accounting for 30%), to obtain the total deviation degree of this behavior chain.

[00174] A formula for calculating the total deviation degree is as follows:

[00175] $$\text{DeviationScore} = w1Dt + w2Ds + w3Df + w4Db$$

[00176] wherein,

[00177] DeviationScore is the total deviation degree;

[00178] w1 is the time deviation value;

[00179] w2 is the spatial deviation value;

[00180] w3 is the frequency deviation value;

[00181] w4 is the behavior chain deviation value;

[00182] Dt is the time deviation weight value;

[00183] Ds is the spatial deviation weight value;

[00184] Df is the frequency deviation weight value; and

[00185] Db is the behavior chain deviation weight value.

[00186] If the total deviation degree is greater than a preset deviation warning threshold, warning information is directly output to a preset receiving terminal; and if it is not greater than the threshold, it is determined to be a normal fluctuation, and no warning is triggered.

[00187] Exemplarily, for the "morning washing up" behavior chain to be detected currently, the regularity reference is as follows: a reference time of the behavior chain is 7:00 (with an allowable fluctuation of ±60 minutes), a reference spatial path is "bedroom bed - bedroom door - bathroom" (with an allowable path deviation of 0.5 meters), a reference frequency is 6.5 times per week (with an allowable fluctuation of ±1 time), and a reference behavior sequence is ("getting up", "walking to the bathroom", and "washing up").

[00188] Actual occurrence is exhibited as follows: the occurrence time is 10:30, with a deviation of 210 minutes from the reference time of 7:00, giving a time-dimension deviation value of (210/60)=3.5; an actual occurrence space is a living room washstand, with a deviation of 8 meters from a reference space, giving a spatial-dimension deviation value of (8/0.5)=16; an actual number of occurrences this week is 0, with a deviation of 6.5 times from the reference of 6.5 times, giving a frequency-dimension deviation value of (6.5/1)=6.5; an actual behavior sequence is ("getting up", "walking to the living room", and "sitting down"), and a behavior chain deviation value, obtained by comparing an actual sequence with a reference sequence, reflects that the action "washing up" has been replaced by "sitting down", and the location is entirely incorrect.

Through qualitative determination, the deviation value in this dimension is very high, with an assumed calculated value of 5.0.

[00189] The weighted calculation gives a total deviation degree of 3.5×0.2 + 16×0.2 + 6.5×0.3 + 5×0.3 = 7.35, which is far greater than a preset deviation threshold of 1.5. Therefore, household behavior abnormality warning information is directly output to a mobile terminal of a user's guardian.

[00190] Based on the above embodiment, by collecting and integrating raw data, and then completing the rapid division of new behaviors in combination with the already-constructed behavior trend model, and finally obtaining a comprehensive deviation degree through multidimensional weighted calculation to trigger a warning, the integrity and accuracy of the raw behavior data are ensured, providing a reliable data foundation for subsequent detection, while also improving the efficiency and accuracy of new behavior division with the aid of existing behavior regularity, thereby avoiding the resource waste caused by repeated division.

[00191] At the same time, through the weighted deviation calculation of the three dimensions of time, space, and frequency, the degree to which a behavior deviates from its original regularity can be comprehensively quantified, avoiding the misjudgment that easily arises from single-dimensional detection, and enabling a warning to be output promptly when the deviation reaches a level of risk, thereby reducing unnecessary false alarms while also ensuring that a truly abnormal behavior can be promptly discovered, providing accurate and reliable abnormality warning capabilities for the household safety monitoring of elderly persons living alone and other special household populations, and effectively improving the practicality and accuracy of a household safety monitoring system.

[00192] Exemplary Apparatus

[00193] FIG. 11 is a schematic structural diagram of an apparatus for constructing a behavior trend model provided by an exemplary embodiment of the present disclosure. The apparatus may be provided in an electronic device such as a server, to perform the method for constructing the behavior trend model according to any of the above embodiments of the present disclosure.

[00194] As shown in FIG. 11, the apparatus 400 may provide an apparatus for constructing a behavior trend model, which includes a data processing module 401, configured to perform association processing on behavior data sets of a plurality of users to obtain standard behavior data subsets corresponding to the users; a data classification module 402, configured to divide the standard behavior data subsets into a plurality of behavior chains based on a preset behavior association rule, the behavior chains being used for combining behavior data in the standard behavior data subsets to form a complete behavior process; and a model construction module 403, configured to determine a stability data set of the behavior chains based on a monitoring period, and construct the behavior trend model based on the stability data set.

[00195] In a possible implementation, the data processing module 401 is specifically configured to: acquire feature information and behavior data sets of a plurality of users, the behavior data sets including movement trajectory data and an action data set associated with the movement trajectory data; determine identity information of the users based on the feature information; perform time alignment and semantic alignment on the movement trajectory data and the action data set to obtain a standard behavior data set; and associate the identity information with the standard behavior data set to obtain the standard behavior data subsets corresponding to the users.

[00196] In a possible implementation, the data processing module 401 is specifically configured to: classify, based on the same time axis, each item of behavior data in the action data sets from different collection terminals, to obtain a plurality of time-aligned data sets; and perform semantic unification on each item of behavior data from different collection terminals in the time-aligned data sets, to obtain the standard behavior data set.

[00197] In a possible implementation, the data classification module 402 is specifically configured to: classify adjacent action behavior data into the same behavior chain, based on a time continuity sub-rule and a behavior logic sub-rule in the behavior association rule; associate occurrence spaces of the adjacent action behavior data based on a spatial continuity sub-rule in the behavior association rule, to determine the same as a continuous path of the same behavior chain; and divide the standard

behavior data subsets into a plurality of behavior chains based on the continuous path of the same behavior chain.

[00198] In a possible implementation, the data classification module 402 is specifically configured to: in response to the time continuity sub-rule, determine that a difference between occurrence times of the adjacent action behavior data is less than a preset threshold, and classify the adjacent action behavior data into the same behavior chain; and in response to the behavior logic sub-rule, determine that the adjacent action behavior data conform to a preset logical relationship, and classify the adjacent action behavior data into the same behavior chain.

[00199] In a possible implementation, the data classification module 402 is specifically configured to: classify the plurality of behavior chains based on a preset behavior chain classification rule, to determine a daily routine behavior chain, a high-frequency behavior chain, and an abnormal behavior chain.

[00200] In a possible implementation, the model construction module 403 is specifically configured to: acquire, based on the monitoring period, a plurality of items of time data and a plurality of items of continuous path data of the behavior chains, as well as an occurrence frequency within a time data period; determine time regularity data of the behavior chains based on the plurality of items of time data and a preset time deviation threshold; determine spatial regularity data of the users corresponding to the behavior chains based on the time regularity data of the behavior chains and the plurality of items of continuous path data; and determine a plurality of occurrence frequencies of the behavior chains based on the plurality of items of time data and the occurrence frequency within the time data period, and determine behavior regularity data based on the plurality of occurrence frequencies, the stability data set including the time regularity data, the spatial regularity data, and the behavior regularity data.

[00201] In a possible implementation, the model construction module 403 is specifically configured to: analyze a fluctuation condition of the behavior chain according to the stability data set, to determine a stability degree of the behavior chain; and obtain the behavior trend model based on the stability data set, in a case where the stability degree of the behavior chain conforms to a preset range.

[00202] The beneficial technical effects corresponding to this exemplary embodiment of the apparatus may be found in the corresponding beneficial technical effects of the exemplary methods section above, and will not be repeated here.

[00203] Exemplary Electronic Device

[00204] FIG. 12 is a structural diagram of an electronic device provided by an embodiment of the present disclosure, including at least one processor 111 and a memory 112. The electronic device may be a vehicle, a server, or a device.

[00205] The processor 111 may be a central processing unit (CPU) or another form of processing unit having data processing capability and/or instruction execution capability, and may control other components in the electronic device 11 to perform desired functions.

[00206] The memory 112 may include one or more computer program products, which may include various forms of computer-readable storage media, such as volatile memories and/or non-volatile memories. The volatile memories may, for example, include a random access memory (RAM) and/or a cache memory. The non-volatile memories may, for example, include a read-only memory (ROM), a hard disk, flash memory, or the like. One or more computer program instructions may be stored on the computer-readable storage medium, and the processor 111 may operate the one or more computer program instructions to implement the method for constructing a behavior trend model and/or other desired functions of the various embodiments of the present disclosure described above.

[00207] In one example, the electronic device 11 may further include: an input apparatus 113 and an output apparatus 114, which are interconnected via a bus system and/or another form of connection mechanism (not shown).

[00208] The input apparatus 113 may further include, for example, a keyboard, a mouse, and the like.

[00209] The output apparatus 114 may output various types of information to the outside, and may include, for example, a display, a speaker, a printer, a communication network, and remote output devices connected thereto, and the like.

[00210] Of course, for simplicity, FIG. 12 shows only some of the components of the

electronic device 11 relevant to the present disclosure, omitting components such as a bus and an input/output interface. In addition, depending on the specific applications, the electronic device 11 may further include any other suitable components.

[00211] Exemplary Computer Program Product And Computer-Readable Storage Medium

[00212] In addition to the above methods and devices, embodiments of the present disclosure may further provide a computer program product, including computer program instructions which, when executed by a processor, cause the processor to perform the steps in the method for constructing a behavior trend model according to the various embodiments of the present disclosure described in the "Exemplary Methods" section above.

[00213] The computer program product may be configured to compile program codes in any combination of one or more programming languages, for performing the operations in the embodiments of the present disclosure, wherein the programming languages include object-oriented programming languages such as Java, C++, and the like, and also include conventional procedural programming languages such as a "C" language or similar programming languages. The program codes may execute entirely on a user computing device, partly on a user device, as a standalone software package, partly on a user computing device and partly on a remote computing device, or entirely on a remote computing device or server.

[00214] Furthermore, embodiments of the present disclosure may further be a computer-readable storage medium having computer program instructions stored thereon, which, when executed by a processor, cause the processor to perform the steps in the method for constructing a behavior trend model in the various embodiments of the present disclosure described in the "Exemplary Methods" section above.

[00215] The computer-readable storage medium may employ any combination of one or more readable media. The readable medium may be a readable signal medium or a readable storage medium. The readable storage medium may include, but is not limited to, for example, an electrical, magnetic, optical, electromagnetic, infrared, or semiconductor system, apparatus, or device, or any combination thereof. More specific

examples (a non-exhaustive list) of the readable storage medium include: an electrical connection having one or more wires, a portable disk, a hard disk, a random access memory (RAM), a read-only memory (ROM), an erasable programmable read-only memory (EPROM or flash memory), an optical fiber, a portable compact disc read-only memory (CD-ROM), an optical storage device, a magnetic storage device, or any suitable combination thereof.

[00216] The basic principles of the present disclosure have been described above in conjunction with specific embodiments. However, it should be noted that the advantages, benefits, effects, and the like mentioned in the present disclosure are merely examples and not limitative, and should not be regarded as necessarily possessed by the various embodiments of the present disclosure. Furthermore, the specific details disclosed above are for the purposes of illustration and ease of understanding only, and are not limitative, and the above details do not limit the present disclosure to necessarily be implemented using the above specific details.

[00217] Those skilled in the art may make various modifications and variations to the present disclosure without departing from the spirit and scope of the present application. Accordingly, insofar as such modifications and variations to the present application fall within the scope of the claims of the present disclosure and their equivalent technologies, the present disclosure is also intended to encompass such modifications and variations.

CLAIMS:

1. A method for constructing a behavior trend model, comprising:

performing association processing on behavior data sets of a plurality of users to obtain standard behavior data subsets corresponding to the users;

dividing the standard behavior data subsets into a plurality of behavior chains based on a preset behavior association rule, the behavior chains being used for combining behavior data in the standard behavior data subsets to form a complete behavior process;

determining a stability data set of the behavior chains based on a monitoring period; and

constructing the behavior trend model based on the stability data set.

2. The method according to claim 1, wherein the performing association processing on behavior data sets of a plurality of users to obtain standard behavior data subsets corresponding to the users comprises:

acquiring feature information and the behavior data sets of the plurality of users, the behavior data sets comprising movement trajectory data and an action data set associated with the movement trajectory data;

determining identity information of the users based on the feature information;

performing time alignment and semantic alignment on the movement trajectory data and the action data set to obtain a standard behavior data set; and

associating the identity information with the standard behavior data set to obtain the standard behavior data subsets corresponding to the users.

3. The method according to claim 2, wherein the performing time alignment and semantic alignment on the movement trajectory data and the action data set to obtain a standard behavior data set comprises:

classifying, based on the same time axis, behavior data in the action data set from different collection terminals, to obtain a plurality of time-aligned data sets; and

performing semantic unification on the behavior data in the time-aligned data sets from different collection terminals, to obtain the standard behavior data set.

4. The method according to claim 1, wherein the dividing the standard behavior data

subsets into a plurality of behavior chains based on a preset behavior association rule comprises:

classifying adjacent action behavior data into the same behavior chain based on a time continuity sub-rule and a behavior logic sub-rule in the behavior association rule;

associating occurrence spaces of the adjacent action behavior data based on a spatial continuity sub-rule in the behavior association rule, to determine the same as a continuous path of the same behavior chain; and

dividing the standard behavior data subsets into the plurality of behavior chains based on the continuous path of the same behavior chain.

5. The method according to claim 4, wherein the determining the adjacent action behavior data as the same behavior chain based on a time continuity sub-rule and a behavior logic sub-rule in the behavior association rule comprises:

in response to the time continuity sub-rule, determining that a difference between occurrence times of the adjacent action behavior data is less than a preset threshold, and classifying the adjacent action behavior data into the same behavior chain; and

in response to the behavior logic sub-rule, determining that the adjacent action behavior data conform to a preset logical relationship, and classifying the adjacent action behavior data into the same behavior chain.

6. The method according to claim 4, after the dividing the standard behavior data subsets into a plurality of behavior chains based on the continuous path of the same behavior chain, further comprising:

classifying the plurality of behavior chains based on a preset behavior chain classification rule, to determine a daily routine behavior chain, a high-frequency behavior chain, and an abnormal behavior chain.

7. The method according to claim 1, wherein the determining a stability data set of the behavior chains based on a monitoring period comprises:

acquiring, based on the monitoring period, a plurality of items of time data and a plurality of items of continuous path data of the behavior chains, as well as an occurrence frequency within a time data period;

determining time regularity data of the behavior chains based on the plurality of

items of time data and a preset time deviation threshold;

determining spatial regularity data of the users corresponding to the behavior chains based on the time regularity data of the behavior chains and the plurality of items of continuous path data; and

determining a plurality of occurrence frequencies of the behavior chains based on the plurality of items of time data and the occurrence frequency within the time data period, and determining behavior regularity data based on the plurality of occurrence frequencies, the stability data set comprising the time regularity data, the spatial regularity data, and the behavior regularity data.

8. The method according to claim 1, wherein the constructing the behavior trend model based on the stability data set comprises:

analyzing a fluctuation condition of the behavior chains according to the stability data set, to determine a stability degree of the behavior chains; and

obtaining the behavior trend model based on the stability data set, in a case where the stability degree of the behavior chains conforms to a preset range.

9. A behavior deviation detection method, comprising:

acquiring a behavior data set of a user;

determining the behavior data set as a plurality of behavior chains based on a behavior trend model; and

calculating a deviation degree of each behavior chain, and outputting warning information in a case where the deviation degree is greater than a preset threshold.

10. An apparatus for constructing a behavior trend model, comprising:

a data processing module, configured to perform association processing on behavior data sets of a plurality of users to obtain standard behavior data subsets corresponding to the users;

a data classification module, configured to divide the standard behavior data subsets into a plurality of behavior chains based on a preset behavior association rule, the behavior chains being used for combining behavior data in the standard behavior data subsets to form a complete behavior process; and

a model construction module, configured to determine a stability data set of the

behavior chains based on a monitoring period, and construct the behavior trend model based on the stability data set.

11. The apparatus according to claim 10, wherein the data processing module is specifically configured to: acquire feature information and behavior data sets of a plurality of users, the behavior data sets including movement trajectory data and an action data set associated with the movement trajectory data; determine identity information of the users based on the feature information; perform time alignment and semantic alignment on the movement trajectory data and the action data set to obtain a standard behavior data set; and associate the identity information with the standard behavior data set to obtain the standard behavior data subsets corresponding to the users.

12. The apparatus according to claim 10, wherein the data classification module is specifically configured to: classifying adjacent action behavior data into the same behavior chain, based on a time continuity sub-rule and a behavior logic sub-rule in the behavior association rule; associate occurrence spaces of the adjacent action behavior data based on a spatial continuity sub-rule in the behavior association rule, to determine the same as a continuous path of the same behavior chain; and divide the standard behavior data subsets into a plurality of behavior chains based on the continuous path of the same behavior chain.

13. The apparatus according to claim 10, wherein the model construction module is specifically configured to: acquire, based on the monitoring period, a plurality of items of time data and a plurality of items of continuous path data of the behavior chains, as well as an occurrence frequency within a time data period; determine time regularity data of the behavior chains based on the plurality of items of time data and a preset time deviation threshold; determine spatial regularity data of the users corresponding to the behavior chains based on the time regularity data of the behavior chains and the plurality of items of continuous path data; and determine a plurality of occurrence frequencies of the behavior chains based on the plurality of items of time data and the occurrence frequency within the time data period, and determine behavior regularity data based on the plurality of occurrence frequencies, the stability data set including the time regularity data, the spatial regularity data, and the behavior regularity data.

14. A computer-readable storage medium, configured to store a computer program

therein, wherein the computer program is used for performing the method for constructing a model according to any one of claims 1 to 8.

15. An electronic device, comprising:

a processor;

a memory, configured to store instructions executable by the processor, wherein

the processor is configured to read the executable instructions from the memory and execute the instructions to implement the method for constructing a model according to any one of claims 1 to 8.