A WEARABLE DEVICE BASED ACUTE ISCHEMIC STROKE MONITORING SYSTEM

Field of the Invention

[01] The invention relates to the technical field of health monitoring, in particular to an acute ischemic stroke monitoring system based on wearable devices.

Background to the Invention

[02] Health monitoring is an important technology. Acute ischemic stroke, as a cerebrovascular disease that seriously threatens human health, has the characteristics of high incidence, high disability rate and high mortality. Timely detection and intervention in the early stage of the disease is very important to improve the prognosis of patients and reduce the harm of the disease. In recent years, the rapid development of wearable devices in the field of health monitoring has brought new hope for the real-time monitoring of acute ischemic stroke. However, the existing wearable stroke monitoring devices generally have core pain points, which seriously restricts its monitoring effect and clinical application value.

[03] At present, the lack of dynamic baseline calibration and individualized differential adaptation is the key problem faced by wearable stroke monitoring devices. The fluctuations of physiological parameters of early symptoms of acute ischemic stroke are non-specific. Small changes in blood pressure, blood oxygen and other indicators are easy to be confused with daily physiological fluctuations. In daily life, blood pressure and blood oxygen will also fluctuate to a certain extent due to factors such as exercise and emotional changes, which makes it extremely difficult to judge whether acute ischemic stroke occurs only based on the changes of these indicators. At the same time, there are significant differences in basic signs between different patients. For example, the differences of baseline blood pressure parameters between hypertensive patients and non hypertensive patients can reach more than 30%. In this case, the use of a fixed threshold early warning system will lead to errors.The reporting rate is too high. For patients with hypertension, The fixed blood pressure threshold may not accurately reflect the blood pressure changes in the occurrence of acute ischemic stroke, which is prone to underreporting. For non hypertensive patients, daily physiological fluctuations may trigger early warning, resulting in a large number of unnecessary false alarms, which not only brings psychological burden to patients, but also wastes medical resources. In order to solve this technical problem, we provide an acute ischemic stroke monitoring system based on wearable devices.

Statement of Invention

[04] The invention aims to provide an acute ischemic stroke monitoring system based on wearable devices to solve the problems raised in the above background technology.

[05] 1. Because the physiological parameter fluctuation of the early symptoms of acute ischemic stroke is easily confused with the daily physiological fluctuation, and the existing equipment is difficult to accurately distinguish. Therefore, this case collects multiple types of original signals through the multimodal signs sensing unit, and the embedded data processing unit uses the composite algorithm for preprocessing, which can comprehensively obtain and accurately process the data, and improve the monitoring accuracy.

[06] 2. Because the basic signs of different patients differ greatly, and the false alarm rate of the fixed threshold early warning system is high, this case generates personalized dynamic baseline curve through the short-term and long-term memory network model built in the dynamic baseline generation unit. The stroke risk assessment unit uses an improved algorithm to calculate the deviation degree, which can adapt to individual differences, reduce the false alarm rate, and timely and accurately warn the risk of acute ischemic stroke.

[07] To achieve the above purpose, an acute ischemic stroke monitoring system based on wearable devices is provided, including the following units:

[08] The multimodal sign sensor unit includes at least three bioelectrical sensors, two optical sensors and one motion acceleration sensor, and each sensor is integrated into the temporal artery patch with a flexible circuit for collecting the original signal;

[09] The embedded data processing unit uses the Wavelet Transform Kalman filter composite algorithm to preprocess the original signal and obtain the user's sign data;

[10] The dynamic baseline generation unit has a built-in time series prediction model based on the long-term and short-term memory network. By continuously learning the user's sign data in the past 72 hours, combined with the ambient temperature and altitude parameters, the personalized dynamic baseline curve is generated. The baseline update cycle is no more than 15 minutes. The sign data includes but is not limited to cerebral blood flow velocity, oxygen metabolism rate and heart rate variability;

[11] The stroke risk assessment unit uses the improved weighted dynamic time warping algorithm to calculate the deviation degree between the current sign data and the dynamic baseline curve in real time. When the collaborative deviation degree of multiple parameters exceeds the preset threshold, an alarm is triggered. The preset threshold is that the systolic blood pressure decreases ≥ 25mmhg and the cerebral oxygen saturation decreases ≥ 15% for 5 minutes.

[12] As a further improvement of the technical scheme, the steps for the multimodal sign sensing unit to collect the original signal are as follows:

[13] The bioelectrical sensors, optical sensors and motion acceleration sensors are initialized and calibrated. According to the set sampling frequency, the bioelectrical sensors collect EEG and ECG signals, the optical sensors collect optical signals related to cerebral blood flow and blood oxygen, and the motion acceleration sensors collect head motion acceleration signals. The collected original signals are preliminarily integrated and time stamped.

[14] As a further improvement of the technical scheme, the embedded data processing unit uses the Wavelet Transform Kalman filter composite algorithm to preprocess the original signal as follows:

[15] The wavelet transform algorithm is used to decompose the original signal and separate the signals with different frequency components. For the separated signals with different frequency components, the Kalman filter algorithm is used for de-noising and data smoothing, and the processed signals with different frequency components are reconstructed to obtain the preprocessed sign data.

[16] As a further improvement of the technical scheme, the training steps of the time series prediction model based on the long-term and short-term memory network in the dynamic baseline generation unit are as follows:

[17] Collect the physical signs data, ambient temperature and altitude data of different users in a variety of environments, build a training data set, and normalize the data in the training data set;

[18] The processed data is divided into training set and verification set according to a certain proportion. The training set is used to train the long-term and short-term memory network model. During the training process, the model parameters are adjusted according to the evaluation results of the verification set until the model converges.

[19] As a further improvement of the technical solution, the steps of generating personalized dynamic baseline curve by the dynamic baseline generation unit are as follows:

[20] Real time access to the user's current signs data, ambient temperature and altitude parameters, input the signs data and current environmental parameters in the past 72 hours into the trained long-term and short-term memory network model, and draw personalized dynamic baseline curves according to the model output results and combined with the preset curve generation rules.

[21] As a further improvement of the technical solution, the dynamic baseline generation unit also performs the following steps after generating a personalized dynamic baseline curve:

[22] Conduct trend analysis on the generated personalized dynamic baseline curve to judge whether the fluctuation of the curve is abnormal. If the fluctuation of the curve is abnormal, automatically re collect the physical signs data of the past 72 hours, the current ambient temperature and altitude parameters, and re input the re collected data into the long-term and short-term memory network model to re generate the personalized dynamic baseline curve.

[23] As a further improvement of the technical scheme, the stroke risk assessment unit adopts the improved weighted dynamic time warping algorithm to calculate the deviation degree as follows:

[24] The current sign data and the dynamic baseline curve were aligned in time series. According to the impact of different sign parameters on the risk of acute ischemic stroke, the weight of each sign parameter was assigned. Based on the assigned weight, the deviation between the current sign data and the dynamic baseline curve was calculated by using the improved weighted dynamic time warping algorithm.

[25] As a further improvement of the technical scheme, the specific steps of triggering early warning by the stroke risk assessment unit are as follows:

[26] The multi parameter collaborative deviation calculated by real-time monitoring, when the systolic blood pressure decreased ≥ 25mmhg and cerebral oxygen saturation decreased ≥ 15% for 5 minutes, it is determined that the multi parameter collaborative deviation exceeds the preset threshold. Once it is determined that it exceeds the threshold, it is immediately triggered by the audible and visual module of the wearable device.

[27] As a further improvement of the technical scheme, the stroke risk assessment unit also performs the following steps during the operation of the system:

[28] Self evaluate the weighted dynamic time warping algorithm regularly, and compare the deviation calculated from the same sign data in different time periods with the actual clinical case data;

[29] According to the evaluation results, if it is found that the deviation between the deviation calculated by the algorithm and the actual situation exceeds the preset range, the algorithm optimization process is automatically started, and the weight distribution of each sign parameter in the algorithm is readjusted by using the historical accumulated sign data and the corresponding clinical diagnosis results;

[30] After retraining and optimization, the algorithm is evaluated again until the deviation calculated by the algorithm is within the normal range from the actual situation.

[31] As a further improvement of the technical scheme, the stroke risk assessment

unit also performs the following steps after triggering the early warning:

[32] Start the emergency data recording mode, set a sampling frequency to collect and store the current physical signs data, automatically call the preset emergency contact information, send a distress signal containing the user location, the current physical signs data summary and early warning information to the emergency contact through the communication module of the wearable device, and store the detailed physical signs data change records before and after the early warning locally for subsequent medical analysis.

[33] Compared with the prior art, the invention has the following beneficial effects:

[34] In an acute ischemic stroke monitoring system based on wearable devices, the dynamic baseline generation unit generates a personalized dynamic baseline curve with the help of the time series prediction model based on the long-term and short-term memory network, combined with environmental factors, and the baseline update cycle is short, which enables the monitoring system to adapt to the differences in basic signs of different patients, overcomes the disadvantages of the traditional fixed threshold early warning, and reduces the false positive rate. The stroke risk assessment unit uses an improved algorithm to calculate the deviation degree in real time to judge the stroke risk. Once the multi parameter collaborative deviation degree exceeds the preset threshold, it will trigger the early warning in time, start the emergency data recording, and send the distress signal operation, which can not only remind patients in the early stage of acute ischemic stroke, but also provide detailed data support for medical rescue, It improves the possibility of patients receiving effective treatment in the early stage of the disease.

Brief Description of the Drawings

[35] Fig. 1 is an overall block diagram of the present invention.

[36] The meaning of each label in the figure is:

[37] 1. Multimodal sign sensing unit; 2. Embedded data processing unit; 3. Dynamic baseline generation unit; 4. Stroke risk assessment unit.

Detailed Description

[38] The technical solutions in the embodiments of the invention will be clearly and completely described below in combination with the drawings in the embodiments of the invention. It is obvious that the described embodiments are only part of the embodiments of the invention, not all of them. Based on the embodiments of the invention, all other embodiments obtained by those skilled in the art without creative work fall within the scope of the invention.

[39] The invention provides an acute ischemic stroke monitoring system based on wearable devices, as shown in Figure 1, including the following units:

[40] The multimodal sign sensor unit 1 includes at least three bioelectrical sensors, two optical sensors and one motion acceleration sensor, and each sensor is integrated into the temporal artery patch with a flexible circuit for collecting the original signal.

[41] The steps for multimodal sign sensing unit 1 to collect the original signal are as follows:

[42] Initialize and calibrate the bioelectrical sensors, optical sensors and motion acceleration sensors, apply standard electrical signals to the bioelectrical sensors, collect output responses, calculate transfer functions and store calibration coefficients. According to the set sampling frequency, the bioelectrical sensors collect EEG and ECG signals, and the optical sensors collect optical signals related to cerebral blood flow and blood oxygen. The optical sensors are calibrated with standard light absorbing materials, and the light source driving current is adjusted to match the output value with the known concentration. The motion acceleration sensors collect head motion acceleration signals. The motion acceleration sensors are in six reference directions (± x, ± y, ± z) in three-dimensional space Put it still, collect the output value and calculate the zero offset and sensitivity matrix, preliminarily integrate all kinds of collected original signals, add time stamp markers, use 32-bit synchronous counters to generate time stamps, embed 16 bit counter values in the head of each sensor data frame, and ensure that the time stamp is synchronized with the sampling time through hardware trigger. In the data fusion stage, use linear interpolation algorithm to resample the asynchronous sampled sensor data to a unified time grid to improve the signal processing accuracy.

[43] The embedded data processing unit 2 uses the Wavelet Transform Kalman filter composite algorithm to preprocess the original signal and obtain the user's sign data.

[44] The embedded data processing unit 2 uses the Wavelet Transform Kalman filter composite algorithm to preprocess the original signal as follows:

[45] The original sign signal contains physiological components and noise with different frequencies. Wavelet transform can decompose it into multi-scale frequency bands for targeted processing. Wavelet transform algorithm is used to decompose the original signal and separate the signals with different frequency components. Kalman filter algorithm is used to denoise and smooth the separated signals with different frequency components, and the processed signals with different frequency components are reconstructed to obtain the preprocessed sign data.

[46] For EEG signal, wavelet basis function is selected to decompose the signal into five frequency bands. For ECG signal, the number of decomposition layers is adjusted to four. Mallat fast algorithm is used to decompose 1024 data frames into approximate coefficients and detail coefficients, which are stored in double buffers. An independent Kalman filter is established for each frequency band. The state vector is set as the true value of the signal, and the observation vector is the noisy measurement value. By calculating the statistical characteristics of the first 50 sampling points, the covariance matrix of process noise and measurement noise is adaptively adjusted, and the signal changes are dynamically tracked Wave band, increase the weight of process noise, enhance the sensitivity to changes in nerve activity, for the frequency band of motion artifacts, improve the weight of measurement noise, suppress random interference, the processed frequency band coefficient needs to be reconstructed into a complete signal, and highlight the characteristics related to stroke. Soft threshold processing is performed on the high-frequency detail coefficient to remove baseline drift and EMG interference The coefficient corresponding to the wave is amplified to strengthen the variation characteristics of EEG activity. The time-domain signal is reconstructed by inverse wavelet transform. The moving average filter is applied to further smooth the cerebral blood flow velocity signal. The dual core processor division is adopted. Core 0 is responsible for wavelet decomposition, and core 1 performs Kalman filtering. Data exchange is realized through shared memory. 1024 point data frames are divided into four 256 sub blocks, which are processed by pipeline. When the former sub block is filtered, the latter sub block is decomposed synchronously, and the floating-point operation is converted to Q15 fixed-point format. The accuracy is retained by dynamic scaling factor to reduce memory occupation and calculation.

[47] The dynamic baseline generation unit 3 has a built-in time series prediction model based on the long-term and short-term memory network. By continuously learning the user's physical signs data in the past 72 hours, combined with the ambient temperature and altitude parameters, the personalized dynamic baseline curve is generated. The baseline update cycle is no more than 15 minutes. The physical signs data include but are not limited to cerebral blood flow velocity, oxygen metabolism rate and heart rate variability.

[48] The training steps of time series prediction model based on long-term and short-term memory network in dynamic baseline generation unit 3 are as follows:

[49] Collect the sign data, ambient temperature and altitude data of different users in a variety of environments, build a training data set, normalize the data in the training data set, establish a data acquisition system, collect the user's sign data through wearable devices, including heart rate, blood pressure and steps, use environmental monitoring devices to obtain the ambient temperature and altitude data, record the data of different users in different scenarios, and integrate these data to form a data set containing a variety of features, which provides sufficient and diversified data for model training, and helps the model better capture the laws in the data.

[50] The processed data is divided into training set and validation set according to a certain proportion. The training set is used to train the long-term and short-term memory network model. During the training process, the model parameters are adjusted according to the evaluation results of the validation set until the model converges. The normalized data are divided according to a certain proportion. The hierarchical sampling method is used to ensure that the distribution of the training set and validation set on different characteristics and user data is similar, so as to ensure the accuracy of model evaluation, provide a scientific data set division for model training and evaluation, and help the model better predict time series data in practical application. The training set is input into the long-term and short-term memory network model, and the parameters of the model are updated using the optimization algorithm to minimize the error between the prediction results of the model and the real value of the training set.And, At the end of each training cycle, input the validation set into the model, calculate the evaluation index of the model on the validation set, adjust the parameters of the model according to the evaluation results of the validation set, and repeat the above training and evaluation process until the performance of the model on the validation set is no longer improved, that is, the model converges, so that the model can better learn the time-series relationship in the data, improve the performance of the model in practical application, and provide accurate prediction for the generation of dynamic baseline.

[51] The steps of generating personalized dynamic baseline curve by dynamic baseline generation unit 3 are as follows:

[52] Real time access to the user's current signs data, ambient temperature and altitude parameters, input the signs data and current environmental parameters in the past 72 hours into the trained long-term and short-term memory network model, and draw personalized dynamic baseline curves according to the model output results and combined with the preset curve generation rules.

[53] The wearable device's built-in sensor can collect the user's physical sign data in real time, including heart rate, respiratory rate and body surface temperature. At the same time, the device's built-in positioning module can be combined with the network to obtain the altitude of the user's location. The environmental monitoring device can be deployed to obtain the user's current ambient temperature and humidity parameters in real time, and transmit the data to the dynamic baseline generation unit 3. It provides a time sensitive and accurate data basis for the generation of personalized dynamic baseline curves, improves the baseline reference value, retrieves the user's physical sign data records in the past 72 hours from the data storage module, and reorganizes them into a time-series data sequence according to the time sequence. The current ambient temperature, altitude and other parameters obtained in real time can be integrated with the historical signs data to form a complete input data group, and normalizes the input data group.And, Make it meet the input requirements of the trained long-term and short-term memory network model, and then input the data into the model, so that the model can predict based on rich information, lay the foundation for generating accurate personalized baseline curves, establish a rule base for curve generation, and process and adjust the data according to the prediction data output from the model and the rules in the rule base. Using data visualization technology, take time as the horizontal axis and physical signs as the vertical axis, draw the processed data into a dynamic baseline curve, and mark the key data points and description information on the curve to generate an intuitive, accurate and personalized dynamic baseline curve that meets the actual needs, so that medical staff or users can intuitively understand the changing trend of physical status.

[54] After generating the personalized dynamic baseline curve, the dynamic baseline generation unit 3 also performs the following steps:

[55] Conduct trend analysis on the generated personalized dynamic baseline curve to judge whether the fluctuation of the curve is abnormal. If the fluctuation of the curve is abnormal, automatically re collect the physical signs data of the past 72 hours, the current ambient temperature and altitude parameters, and re input the re collected data into the long-term and short-term memory network model to re generate the personalized dynamic baseline curve.

[56] The sliding window algorithm is used to set the window size to calculate the mean value and standard deviation of curve data in each window. The polynomial fitting or exponential smoothing method is used to fit the curve to obtain the trend line of the curve. By comparing the deviation degree between the actual curve and the trend line, the fluctuation trend of the curve is judged. Combined with the research results of the fluctuation range of normal physiological parameters in the medical field, the normal fluctuation threshold range of different physical signs data curves is set to realize the dynamic monitoring of the baseline curve, detect the possible abnormal fluctuations in time, and compare the curve data at each time point with the corresponding normal fluctuation threshold range. If the data exceeds the threshold range, the point is marked as an abnormal point, and the number and distribution of abnormal points are counted. If the number of abnormal points exceeds the set value in a continuous time interval,threshold, If the proportion of abnormal points in three consecutive windows exceeds 40%, the fluctuation of the curve is determined to be abnormal. Considering the persistence and amplitude of the curve fluctuation, if the curve continues to rise or fall and deviates from the trend line by more than a certain degree, such as 2 times of the standard deviation, it is also determined to be abnormal fluctuation, which provides a reliable decision-making basis for the subsequent re generation of the baseline curve, starts the data re acquisition program, obtains the physical signs data of the past 72 hours again through wearable devices and environmental monitoring devices, including heart rate, blood pressure, steps, current ambient temperature and altitude parameters, strictly cleans the recollected data, removes duplicate and wrong data records, and normalizes them to ensure that the data format and range meet the input requirements of the long-term and short-term memory network model, Input the processed data into the trained long-term and short-term memory network model again, and use the model to process and predict the new data. The baseline curve generated based on the new data can more accurately reflect the current actual situation of the user, improve the effectiveness and reference value of the dynamic baseline. According to the prediction results output by the model, combined with the preset curve generation rules, optimize the prediction data, and use the data visualization technology to redraw the processed data into a personalized dynamic baseline curve with time as the horizontal axis and physical sign data as the vertical axis. Mark the data source and the time information of regeneration on the newly generated curve to facilitate subsequent viewing and analysis, so as to ensure that the generated baseline curve can reflect the latest status of the user in real time and maintain the timeliness and accuracy of the curve.

[57] The stroke risk assessment unit 4 uses the improved weighted dynamic time warping algorithm to calculate the deviation degree between the current sign data and the dynamic baseline curve in real time. When the collaborative deviation degree of multiple parameters exceeds the preset threshold, an alarm is triggered. The preset threshold is that the systolic blood pressure decreases ≥ 25mmhg and the cerebral oxygen saturation decreases ≥ 15% for 5 minutes.

[58] The stroke risk assessment unit 4 uses the improved weighted dynamic time warping algorithm to calculate the deviation degree as follows:

[59] The current sign data and the dynamic baseline curve were aligned in time series. According to the impact of different sign parameters on the risk of acute ischemic stroke, the weight of each sign parameter was assigned. Based on the assigned weight, the deviation between the current sign data and the dynamic baseline curve was calculated by using the improved weighted dynamic time warping algorithm.

[60] The linear interpolation method is used to resample the data, unify the current signs data and the dynamic baseline curve to the same time interval, and use the sliding window technology to find the best alignment starting point in the time series. By calculating the similarity of the two groups of data at different starting points, the starting point with the highest similarity is selected as the alignment benchmark to realize the precise alignment of the time series, and ensure that the deviation calculation results truly reflect the difference between the signs data and the baseline. A medical expert evaluation team is established to determine the influence coefficient of the signs parameters on the risk of stroke in combination with the clinical research results and a large number of case data. The weight of the signs parameters is quantified by AHP, and a judgment matrix is constructed to compare the relative importance of different signs parameters. The weight value of each parameter is obtained by matrix operation, The consistency test was carried out to ensure the rationality of weight distribution, and the weight value was updated regularly. According to the latest medical research progress and clinical data feedback, the weight of each sign parameter was dynamically adjusted to ensure that the weight system kept pace with the times, improve the accuracy of stroke risk assessment, make the assessment results more consistent with the actual risk status, and provide a more reliable basis for clinical decision-making. The weighted distance matrix was constructed. Based on the distance calculation of the traditional dynamic time warping algorithm, the difference of sign data at each time point was multiplied by the weight of the corresponding parameter, and the path backtracking optimization strategy was adopted. When searching for the optimal alignment path, the path branch with large weight impact was preferred to avoid the wrong alignment caused by the fluctuation of secondary sign data. By recording the cumulative weighted distance on the path, Find the minimum cumulative weighted distance path from the starting point of the matrix to the end point, and take the total distance value of the minimum cumulative weighted distance path as the deviation degree between the current sign data and the dynamic baseline curve. The larger the value, the farther the current sign data deviates from the baseline, and the higher the stroke risk may be. Improving the accuracy and effectiveness of stroke risk assessment is helpful to early detection of potential risks.

[61] The specific steps for triggering the early warning in stroke risk assessment unit 4 are as follows:

[62] The multi parameter collaborative deviation calculated by real-time monitoring, when the systolic blood pressure decreased ≥ 25mmhg and cerebral oxygen saturation decreased ≥ 15% for 5 minutes, it is determined that the multi parameter collaborative deviation exceeds the preset threshold. Once it is determined that it exceeds the threshold, it is immediately triggered by the audible and visual module of the wearable device.

[63] Establish a real-time data acquisition and transmission channel, collect systolic blood pressure, cerebral oxygen saturation and other sign data at a frequency of 1-2 times per second through wearable devices, and synchronously transmit them to stroke risk assessment unit 4. The assessment unit continuously calls the improved weighted dynamic time warping algorithm to calculate the collaborative deviation of multiple parameters between the current sign data and the dynamic baseline curve, update and store the calculation results every 30 seconds, provide real-time and accurate data support for subsequent threshold judgment and early warning trigger, improve the timeliness of risk early warning, and preset the abnormal standard of key parameters: reduce systolic blood pressure by ≥ 25mmhg And the decrease of cerebral oxygen saturation ≥ 15% is set as the core abnormal index. At the same time, a 5-minute duration threshold is configured. The sliding time window mechanism is used to analyze the sign data in real time. When the continuous records in the window meet the abnormal standards of systolic blood pressure and cerebral oxygen saturation, it is determined that the collaborative deviation of multiple parameters exceeds the preset threshold. The binary model is trained with the historical stroke case data to take the current sign data and deviation as the input, and output the probability of whether to trigger the early warning. When the probability exceeds the set threshold, the credibility of the judgment results is enhanced, and the misjudgment rate of early warning is reduced, so as to ensure that the early warning is triggered only when the high-risk signs continue to be abnormal, so as to improve the practicability of the early warning system. When the collaborative deviation of multiple parameters exceeds the threshold, The stroke risk assessment unit 4 immediately sends an early warning command to the wearable device, which contains the early warning level and abnormal parameter information. After the wearable device receives the command, it starts the sound and light module: sends out high-frequency flashing red lights, plays a rapid beep alarm sound, and displays abnormal parameters and early warning prompts in large font on the device screen, such as "systolic blood pressure and cerebral oxygen saturation continue to be abnormal, there is a risk of stroke!" and the early warning information is synchronously pushed to the associated mobile app, home monitoring terminal and medical institution emergency platform to ensure that all parties can obtain the early warning information in time, so as to win precious time for emergency treatment, reduce the risk of stroke or reduce the severity of the disease.

[64] The stroke risk assessment unit 4 also performs the following steps during system operation:

[65] Self evaluate the weighted dynamic time warping algorithm regularly, compare the deviation calculated from the same sign data in different time periods with the actual clinical case data, establish a time slicing mechanism, automatically divide the historical data segments by week/month, select the sign data samples with complete clinical diagnosis results in each time period, run the weighted dynamic time warping algorithm, calculate the deviation from the same sign data, and compare it with the stroke risk level in the actual clinical case, use kappa consistency test, area under ROC curve (AUC) index to quantify the consistency between the algorithm prediction and clinical diagnosis, build the algorithm performance evaluation report, record the evaluation index, typical deviation cases and trend analysis chart in each cycle, and store it in the system log;

[66] According to the evaluation results, if it is found that the deviation between the deviation calculated by the algorithm and the actual situation exceeds the preset range, the algorithm optimization process will be automatically started, and the weight distribution of each sign parameter in the algorithm will be readjusted by using the historical signs data and the corresponding clinical diagnosis results. After retraining and optimization, the algorithm will be evaluated again until the deviation calculated by the algorithm and the actual situation are within the normal range.

[67] Set the deviation threshold monitoring module. When the AUC value of two consecutive evaluation cycles is lower than 0.75 or the kappa coefficient is lower than 0.6, trigger the optimization process, call the historical data warehouse, extract the multi parameter sign data of ≥ 5000 cases with clear clinical diagnosis results in recent 12 months, and use the integrated learning method to redistribute the weight, as follows:

[68] The Gini index contribution rate of each sign parameter to stroke risk prediction is calculated. The Gini index is used to measure the important index of each sign parameter to stroke risk prediction. The optimal weight combination of each parameter is determined through cross validation. The weight configuration that can maximize the prediction accuracy is searched in the parameter space. The expert knowledge constraint is introduced to ensure that the new weight distribution conforms to clinical cognition, so that the algorithm weight can adapt to the latest clinical characteristics, and improve the prediction accuracy in high-risk scenarios. A single optimization may fall into local optimization. Iterative validation can ensure that the algorithm achieves stable and excellent performance after multiple rounds of adjustment, forming a closed-loop optimization system. The rolling validation strategy is used to divide the historical data into training set, validation set and test set in time order. After each optimization, the validation evaluate performance on set if AUC If the increase is ≥ 0.03, the new weight will be accepted. Otherwise, it will be rolled back to the previous version, and multi-dimensional verification will be implemented. The performance of the algorithm will be tested in different time windows. The performance of the algorithm in subgroups will be evaluated according to age, gender and basic disease dimensions. The focus will be on the "missed diagnosis" cases with high-risk clinical diagnosis but low-risk initial prediction of the algorithm. The weight of relevant parameters will be adjusted accordingly. When the AUC improvement of three consecutive rounds of optimization is<0.01 and the kappa coefficient fluctuation is<0.05, the convergence of the algorithm will be determined and the optimization will be stopped.

[69] After triggering the warning, the stroke risk assessment unit 4 also performs the following steps:

[70] Start the emergency data recording mode, set a sampling frequency to collect and store the current physical signs data, automatically call the preset emergency contact information, send a distress signal containing the user location, the current physical signs data summary and early warning information to the emergency contact through the communication module of the wearable device, and store the detailed physical signs data change records before and after the early warning locally for subsequent medical analysis.

[71] When the early warning is triggered, the system will immediately increase the collection frequency of physical signs data from the conventional 1-2 times per second to 5-10 times per second to ensure that more subtle changes in physiological parameters are captured. The ring buffer storage mechanism is used to open up a fixed size of storage space in the memory, and the data is recorded in a first in first out manner. When the storage space is about to be full, the data will be automatically synchronized to the local storage device to ensure the continuity of data recording, the collected data will be marked in real time, and the early warning trigger time stamp and data type label will be added to facilitate the subsequent rapid search and analysis. An encrypted emergency contact information database will be established to store the contact name, telephone number, relationship with patients and other information, and users will be supported to add, modify and delete contacts at any time.After triggering, the system automatically reads the emergency contact information, Send a distress signal to all emergency contacts through the communication module of the wearable device. The content of the distress signal includes the user's current precise location, key signs data summary and early warning information. In order to ensure the accurate transmission of information, the system automatically retransmits the distress signal every 30 seconds until the contact's confirmation reply is received, so that patients can receive timely and effective treatment within the golden treatment time. Create a special alert data folder in the local storage device, and name the subfolder of each alert event with the time stamp, which is used to store all the data of the corresponding event. In addition to the high-frequency collected signs data, it also records the multi parameter collaborative deviation calculation process data, algorithm judgment log and other information within 10 minutes before and after the alert trigger, forming a complete event recording chain, Using compression encryption technology to process the stored data, while ensuring the integrity of the data, it protects the privacy and security of patients, sets data access rights, and only authorizes medical personnel and system administrators to view the relevant data, which helps medical personnel to deeply understand the rules of disease development, improve the level of stroke diagnosis and treatment, and also provides a data basis for the continuous improvement of stroke risk assessment algorithm.

[72] In the invention, the multimodal sign sensing unit 1 integrates multiple sensors to collect the original signal, the embedded data processing unit 2 uses the Wavelet Transform Kalman filter composite algorithm to preprocess and obtain the sign data, the dynamic baseline generation unit 3 uses the short-term memory network model to generate a personalized dynamic baseline curve combined with environmental parameters, and the update cycle does not exceed 15 minutes. The stroke risk assessment unit 4 uses the improved weighted dynamic time warping algorithm to calculate the deviation degree, triggers an early warning when the preset threshold is exceeded, and performs emergency operations. The invention effectively reduces the false alarm rate and realizes the real-time and accurate monitoring of acute ischemic stroke through multimodal data acquisition, personalized baseline generation and accurate risk assessment.

[73] The above shows and describes the basic principles, main features and advantages of the invention. Those skilled in the industry should understand that the invention is not limited by the above embodiments. The above embodiments and descriptions are only the preferred embodiments of the invention and do not need to limit the invention. Without departing from the spirit and scope of the invention, the invention will have various changes and improvements, which fall within the scope of the invention required to be protected. The scope of protection claimed by the invention is defined by the appended claims and their equivalents.