Scholar Publishing Group
International Journal of Multimedia Computing
https://doi.org/10.38007/IJMC.2022.030302
ISSN 2789-7168 Vol. 3, Issue 3: 14-32

Wearable Robot Sensor Signal Prediction Algorithm Analysis and Study based on Particle Filtering

Yanli Zhang

Army Engineering University, Shijiazhuang 050000, Hebei, China

aier20712@126.com

Keywords: Sensor Signal, Real-time Prediction, Particle Filter Optimization, Frequency Multiplication

Abstract: In this paper, a simple platform for exoskeleton booster is designed and built. The sensing device uses static torque sensor for real-time signal acquisition and feedback. In order to remove signal impurities, this paper designs simple and effective impurity filtering circuits and algorithms. The filtered sensor signal was analyzed by unit root test to determine its stability, and the initial model was determined by ACF and PACF order method. According to the characteristics of the sensor signals of this system, the MWDAR model is verified by the model order and the short-term sliding window size. Using the existing MWDAR model, the prediction value is low. Because of the low prediction accuracy, this paper proposes to introduce particle filter algorithm to optimize, and design a new sensor signal time series prediction algorithm, and simulate it through MATLAB software. Verify the effectiveness of the designed algorithm. Due to the characteristics of the force sensor, the dynamic response frequency is significantly lower than the human neural response frequency. At the same time, after the particle optimization algorithm is used, the calculation amount is increased, which makes the prediction delay. In response to these problems, this paper uses frequency doubling technology, which can double the dynamic response frequency of the booster sensing system, thus providing a basis for accurate, real-time signal prediction.

1. Introduction

1.1. Research Background and Significance of the Topic

With the continuous development of technology, robots have become more and more recognized. With robots, people can do a lot of dangerous work, such as bomb blasting and mine detection. However, is it possible to create a kind of powerful mechanical assistance that is capable of interacting with humans and has the unique mechanical power that is unique to robotic devices? With the constant exploration and research, the idea of exoskeleton robots came into being. Movies such as Iron Man, Pacific Rim, and Bliss Space showcase the power of exoskeleton robots. In particular, "The Bliss Space", the protagonist Max in a work accident, was subjected to strong radiation, causing severe deterioration of physiological functions, and the ability to live a sharp decline. It is necessary to use drugs to resist, and the adverse reaction is to shorten the life to one week. In order to avoid a sharp shortening of life, after installing an exoskeleton mechanism connected to the brain nerve, the movement of the mechanical device is controlled by the brain to make it work normally, and the mechanical device also gives him more powerful power. . The big sale of these sci-fi movies is undoubtedly because of the embarrassment of people in the future. Although all of the above are just hypothetical things about new things, it is not difficult to see that wearable exoskeleton robots have an enormous role in expanding human athletic ability, and the research and development of exoskeleton robots is of great significance.

After the Second World War, the generation of “baby boomers” has gradually entered an aging period, and the problem of aging in the world has become increasingly serious, which has attracted great attention from all countries, including China. At present, Chinese politicians have proposed a plan to delay retirement or delay payment of pensions to deal with China's aging problem. It is conceivable that the problem of China's aging problem is serious. Old people suffer from the deterioration of physiological functions due to organ failure, especially the deterioration of leg function, which will make them inconvenient to move, which may cause life to be self-care, and may even be hurt in the mind. Among the elderly aged 65 and over, falling due to inconvenience in the legs and feet is the main cause of morbidity and mortality in the elderly. From 2005 to 2006, nearly 66,800 Australian elderly people fell into hospitals because of falling [1]. In our country, according to international standards, nearly 30 million elderly people fall down each year because of their legs and feet. Among them, nearly 1.8 million people have broken because of falls.

The exoskeleton robot is a mechanical power device that attaches to the body surface of a person. The person provides the device to guide the braking power, and the exoskeleton device exerts its unique strong mechanical power, human-computer interaction, coordination, and work together. . The realization of the robot's power-assisting effect is mainly divided into two parts: the prediction of human motion intention and the drive control of the controller. The drive control of the controller relies on the accurate prediction of the motion intent, and the timing prediction algorithm is directly related to the advantages and disadvantages of the robot's power assist effect. Inaccurate predictions of human body movements are not only unable to achieve the effect of assist, but become obstacles in the course of human action.

1.2. Research Status and Development Trends at Home and Abroad

1.2.1. Development Status of Exoskeleton Robots

The concept of exoskeleton robots [3-6] has been extended from bionics research. At present, the research on exoskeleton robots has made great breakthroughs, and its application field has also shifted from the military field to the civilian field. Scientists have developed a number of exoskeleton robots to effectively help people with their normal daily life and work. The wearable power-assisted robot is a kind of exoskeleton robot. It attaches to the surface of the human body, collects the motion information of the human body through the sensing system in the device, and feeds back the information. The system fits according to the feedback information to carry out the next movement of the human body. The intent is predicted, and then the control system controls the mechanical brakes to finally achieve the boosting effect.

The earliest start of exoskeleton robotics began in 1966, when the United States conducted research and development of Hadiman power-assisted robots. The main purpose of the study was to reduce the weight of the soldiers during the march by relying on the mechanical load-bearing capacity of the booster device, thereby reducing the physical exertion of the soldiers. Due to the limited factors, robot research is still not ideal and is still in the research and development stage. Although Hardyman's research and development was not successful, the research on exoskeleton robots has been greatly promoted, and it has gradually been recognized by everyone, and it has also set off a new wave of research.

Domestic research on exoskeleton robots has not achieved much development due to late start, but it has also achieved some results. Hefei Institute of Intelligent Machinery of Chinese Academy of Sciences has developed a lower limb walking assisted exoskeleton robot [8]; Zhejiang University has developed a multi-degree of freedom lower extremity exoskeleton assistant robot [9]; Harbin Engineering University mainly studies lower limb rehabilitation exoskeleton robots, A number of models have been developed.

1.2.2. Trends in Time Series Prediction Research

Prediction [2] is based on known events to speculate on future events that will occur in the future, and it plays a pivotal role in life. The main purpose of the forecast is to achieve risk aversion and decision making. For example, earthquake prediction is to reduce economic losses and casualties caused by natural disasters. The role of the weather forecast is to better define the next itinerary. Time series prediction is based on historical data information obtained in the past time to predict future time information. It predicts the data of future time through model fitting through the inherent and intrinsic characteristics between the data and the system disturbance relationship between the data domains. The real time series is affected by many factors, and thus has irregular characteristics, which can be roughly divided into four types [3]: (1) periodic variation, which refers to the fluctuation of the phenomenon according to a fixed period; (2) The cyclical change refers to the fluctuation of the phenomenon according to the unfixed periodicity; (3) the change of the trend, which means that the phenomenon changes with time, a fluctuation of rising, steady or falling; (4) random fluctuation, It means that the phenomenon is affected by external factors and shows unstable fluctuations.

The early stationary time series prediction models mainly include Auto Regressive (AR) and Moving Average (MA) models. With the passage of time, through the joint efforts of countless experts and scholars, the time series modeling and prediction technology has been greatly developed. In 1970, Box and Jenkins' book "Time Series Analysis: Forecasting and Control" [4] was published. Domestically, in 1986, Xiang Jingjun's "Dynamic Data Processing - Time Prediction Analysis" [5] and Shi Renjie's "Time Series Analysis Guide" [25], was the earliest book on time series prediction.

2. Overview of Time Series Prediction Related Technologies

2.1. Introduction to Time Series Analysis

The time series [6] is a series of observations based on chronological order. This time-sensitive observation is also called dynamic data. Time series analysis is included in the general theory of statistics, and its important theoretical basis is the interdependence between adjacent data in time series. From the perspective of sequence dependence, it analyzes and studies the development law of its data, and nests through the existing mature time series model. After parameter estimation and order determination, it can fit the time series data well. Develop a regular model and finally use the successfully fitted model to predict the future course of the sequence.

From the perspective of historical development, the first thing to do in the time series analysis is to study the stability of time series data. The so-called stationarity is the requirement that the curve obtained by fitting the historical observation data can be used in the following period of time. Some states "inertia" continue to execute. If the observed value is not stable, it indicates that the currently fitted curve does not have the "inertia" continuous characteristic, that is, the current fitted model is different from the model fitted by the future observation, which will eventually lead to inaccurate prediction. Sex. The stationary process can be strictly divided into strict stability and wide stability: only when the sequence maintains all statistical equilibriums in the probability characteristics in the process, and does not change with time, the sequence is called strict and stable; while the wide and stable is similar to strict and stable. But the mathematically weaker definition, which is a kind of stationarity defined by the statistic of the sequence, only needs to ensure that the sequence is low-order stationary to ensure that the main properties of the sequence are approximately stable. The stationary sequence is often referred to as a weakly stable sequence, and the models commonly used to fit it mainly include autoregressive AR models, moving average MA models, and autoregressive moving average ARMA models.

The earliest study of time series analysis dates back to 1927, when Yule pioneered the linear autoregressive AR model. Four years later, another digitist, Walker, extended the AR model to the general AR(s) model, which became the main line of development for the AR model. The MA model was first proposed thanks to Slutzky; in 1938, Wold took the above-mentioned main theoretical ideas about the development of time series with Khinchin and Kolmo. Kolomogorov's probability theory, stochastic process axioms, and other related fields of frequency domain analysis methods combine to propose the ARMA model, which lays the foundation for the study of time series analysis methods, and also for later research. Development has helped a lot. In 1970, Box and Jenkins's "Time Series Analysis: Forecasting and Control" came out, which is a new milestone in the development of time series analysis [10]. The book presents the ARIMA model and provides detailed analysis of the time series, predictions, and systematic methods for ARIMA modeling, parameter estimation, and model diagnosis. The system method is referred to as the B-J method. Then, with the rapid development of information processing technology, the time series modeling method has been further improved in theoretical research. At the same time, the parameter estimation algorithm and the model ranking method have been greatly improved. As time series modeling technology matures, its application fields are becoming more and more extensive. Its role is mainly to predict the future development trend of events, so as to better plan or reduce economic losses and casualties caused by disasters. Such as weather forecast, stock trend forecast in the stock market, earthquake precursor forecast and crop pest and disease forecast.

2.2. Time Series Model and Modeling Method

2.2.1. Time Series Basic Model

In production and life, to monitor an event X(t), we will obtain corresponding discrete data at a series of times t1, t2,..., tn(t1≤t≤tn), and these discrete data are composed of The sequence set X(t1), X(t2), ..., X(tn) is called a time series and is represented by {X(t)}. The value of t can be positive or negative. Taking the current time as the statistical benchmark, the observations generated before the current time can be considered to produce a negative time value, and these observations are called historical data; the observations generated after the current time can be considered as the resulting The time value is positive and the corresponding observations are called future data. Time series analysis can be divided into frequency domain analysis and time domain analysis according to different data processing methods. The frequency domain analysis is based on spectral analysis. The analysis method is more complicated, and the analysis results are relatively abstract, which is not easy to explain intuitively. At the same time, the frequency domain analysis method requires researchers to have a strong data and physical basis, so it has a lot of limitations. Currently used more time domain analysis methods.

2.2.2. Time Series Prediction Model Identification

The first thing that needs to be done in time series analysis and prediction is the identification of the model. Through the current set of observation data and the existing model reference, a curve model that can well fit the development trend of the data is sought. The model identification work is a kind of A rough process. When an in-depth study of a model is done, the work to be done is the order determination and parameter estimation of the model to determine whether the current model is suitable.

The ARIMA model proposed by Box and Jenkins is the most commonly used time series model for stationary and non-stationary time series. The ARIMA model performs an Automatic Direction Finder (ADF) based on the observed data to determine its stationarity. If it is a non-stationary process, it performs a differential operation. If the d-th difference Wtt of a time series { t Y } is a stationary ARMA process, then {tY} is called the autoregressive moving average summation model. If t W obeys the ARMA(p, q) model, then {t Y} is the ARIMA (p,d,q) process, where p is the number of autoregressive terms, q is the moving average number, and d is the time The number of differential operations required to convert a sequence from a non-stationary time series to a stationary time series. In practice, usually d takes 1 or at most 2.

Next, what needs to be done is the sliding average order q and the autoregressive order that are suitable for the preliminary determination of the ARIMA model transformed into a stationary process. The BJ method mainly uses the autocorrelation function (ACF) and bias of the observed values. The statistical characteristics of the correlation function (PACF) are roughly determined, and the subsequent work is consistent with the ARMA(p,q) order.

Since the introduction of Box and Jenkins's theory, researchers have proposed many other model identification methods through continuous research, such as Akaike's Information Criterion (AIC) and Bayesian Information Ceriterion (BIC). The most studied is the AIC guidelines.

2.2.3. Model Ordering Method

The initial determination of the model is the beginning of the modeling, and then the order and parameters of the model must be determined, which is a refinement process. Only when the model's order and parameters are all determined, the modeling work is truly completed, and the established model can be used for subsequent time series prediction. There are many fixed-order methods in the current model. The following are some common introductions: (1) Residual variance diagram The residual variance diagram is a sequence obtained by subtracting the predicted value from the actual value. Calculate its variance to determine its order. The rule is that the smaller the residual variance, the more reasonable the corresponding order.

(1) ACF and PACF grading methods In the previous section, we have outlined the rules for ACF and PACF grading. Box and Jenkins recommend using the order information provided by the partial correlation function to determine the order of the AR model part. Because there is a partial model coefficient p of the AR model, the partial correlation function between tp Yand p Y can be obtained. When k>p, the partial correlation coefficient is zero, so only the partial correlation function is fitted. The curve relationship of the k-order lag can roughly determine the order of the model.

(2) F-test fixed-order method The F-test is used to test whether the population variances of two variables are equal. It is a hypothesis test method. In the model test, it mainly compares the variances produced by the two models. Judging to determine if there is a significant difference, it was proposed by the British statistician Fisher.

For example, for the ARMA (p, q) model and the ARMA (p+1, q+1) model, use F to test whether there is a significant difference in the sum of the residuals between the two models. The specific operation method is: The ARMA(p,q) model is fitted to the ARMA(p+1,q+1) model, and their sum of squared residuals is recorded as Q0 and Q1, respectively, and the model degrees of freedom corresponding to the two models are respectively For df0 and df1, N is the number of observations.

For the significance level, the critical value F can be obtained. If FF, the original hypothesis is rejected. It is considered that there is a significant difference in the fitting accuracy of the two models, and the ascending order is inappropriate; and when FF I think that there is no significant difference in the fitting accuracy between the two models, and the ascending order is reasonable.

(3) criterion function ordering method

All of the above methods are based on the overall variance of the observed values to determine the rationality of the model's order, which is an important indicator to describe a good or bad model. The maximum likelihood estimate for the population variance indicates that the least squares and criteria are equivalent to the minimum variance criterion for the residual. In general, the smaller the value of the population variance, the better the accuracy of the fitted model fits. Usually adding a model's parameters will result in a smaller population variance of 2. On the surface, it seems that the accuracy of the model fit is improved, but this change is small and almost negligible, but its price is a loss of freedom. degree. As a good model, it should be as simple as possible while ensuring its good accuracy, and reduce the 2 to the appropriate degree with a small number of parameters.

The best criterion for model ordering is to consider both the accuracy of fitting the observations and the number of parameters to be determined in the model, so that a reasonable trade-off can be made between the two. In 1971, Japanese scholar Akaike proposed the Final Prediction Error (FPE), which is used to identify the AR model order. In 1973, based on the FPE guidelines, it was promoted to identify the ARMA model, which is the AIC standard we are now familiar with. Although the AIC criterion can provide a lot of convenience for the order estimation of the time series model, it still has some shortcomings - for the coincidence estimation of the model order, the AIC criterion cannot be provided, that is, when N, The order of the model obtained by the AIC criterion does not converge to the real order, but has a certain gap with the real order, generally higher than the real order. To compensate for the shortcomings of the AIC guidelines, Schwarz proposed the BIC guidelines based on the AIC guidelines.

The residual of the model residual can be calculated by the formula. The FPE method criterion is implemented by gradually increasing the model AR(p) from p=1 and finally determining the model order. The specific steps are as follows:

(1) At the beginning, the observation data is input, and the upper limit of the order p is

determined by the number of observation data. According to experience, when the number of observations is in the range of 100-200, the upper limit is 2N/ln2N; when N is within 100, the arithmetic square operation of N can be simply performed, and the obtained result is taken as the upper limit value;

(2) Initialize, let p=1, calculate its FPE(p) value;

(3) Add the p value to 1, calculate its FPE(p) value, and compare it with FPE(p-1);

(4) If FPE(p)<FPE(p-1), continue with steps (2) and (4). If FPE(p)>FPE(p-1), output p-1 as its model order. And output the parameters of the response.

3. Design and Analysis of Exoskeleton Booster Robot Prediction System

3.1. System Overall Design Framework

The sensor generates raw data, and amplifies the generated raw signal data of the sensor through an amplifying circuit, and then performs signal filtering through the designed parallel capacitor filtering circuit to remove impurities, and finally uses the multi-function signal acquisition card to collect the processed signal data, and uploads.

The main work of the software is further filtering of signals and signal prediction modeling and prediction. First, the data is received through the serial port, and then the data is designed to be filtered, so that the data is stable and smooth, and then the processed data is processed to model, determine the model order, and finally rely on the established time prediction model for future force signal values. The predictions are made and the sliding window is moved backwards.

3.2. System Hardware Design

The system hardware mainly includes three modules: a signal output module, a micro filter module, and a data acquisition module. The main functions are: generating the original force signal through the static torque sensor and amplifying through the sensor signal amplifier; the amplified signal is filtered by the designed capacitor group for impurity signal; and the force signal is collected by the NI USB-6009 signal acquisition card.

3.2.1. Signal Output Module

The main content of the signal output module is the generation and output of signals and the expansion of signals. The signal is collected using a static torque sensor. The specifications are as follows:

Rated load: 2~3000N.m

Creep: ±0.05 %FS /30min

Input impedance: 380 ± 10 Ω or 750 ± 30 Ω

Output impedance: 350 ± 3 Ω or 700 ± 5 Ω

Insulation resistance: >5000 MΩ

Safety overload: 150% FS ·

Bridge voltage: 10VDC, 12VDC, 24VDC

Output signal: mv/v, 4~20mA, 1~5V, 0~5V

Wiring method: power (+) red line power (-) green line

Output (+) yellow line output (-) white line

The static torque sensor works on the principle of resistance strain. The sensor has one end fixed and the other end can be twisted as the leg joint bends. When operating, the dual DC regulated power supply, provides 24V DC stabilized voltage to the sensor. When the static torque sensor bends with the leg and causes one end of the sensor to twist, the resistance changes, and the voltage signal value changes accordingly. The voltage signal is the raw signal data we need. The raw data is amplified by a signal amplifier and uploaded to the micro-filter module for further processing.

3.2.2. Microfiltration Module

When the regulated DC power supply is powered, the signal waveform glitch problem occurs due to some interference factors. At the same time, since the sampling frequency of the data in the system is high and the fluctuation of the value is small, the generation of the glitch is compared in the system. The big impact, how to minimize signal glitch and eliminate impurity waves is a very important issue. A filter is a network of parametric resistors, capacitors, and inductors that perform different functions depending on the parameters of the resistors, capacitors, and inductors. According to the passband classification, the filter mainly has a band rejection filter, a band pass filter, a high pass filter, and a low pass filter.

The low-pass filter is the most commonly used filter. Its function is to suppress high-frequency signals and pass low-frequency signals, that is, pass low frequencies and block high frequencies. On the contrary, Qualcomm's role is to suppress low-frequency signals through high-frequency signals, that is, high-frequency, low-frequency.

The function of the band-stop filter is to attenuate a specific range of frequency signals to an extremely low level by most frequency signals. The input voltage is simultaneously passed through the low-pass filter and the high-pass filter, and then the two voltages of the output are summed, which is a simple band-stop filter. In contrast to the bandpass filter, it acts to block signals outside a specific frequency range by frequency signals within a specific range.

3.2.3. Data Acquisition Module

Signal data acquisition, the NI USB-6009 used in this article is a 14-bit, 48kS/s multi-function data acquisition card. The two sides of the device are digital channel and analog channel. The specifications of the acquisition card are as follows:

Bus type: USB
Operating System / Object: Windows, Linux, Mac OS, Pocket PC
Measurement type: voltage
Analog input: Analog output:
Number of channels: 4 differential channels, 8 single-ended channels Number of channels: 2
Resolution: 14bits Resolution: 12bits
Sampling rate: 48kS/s
Maximum voltage range: -10V~10V Maximum voltage range: 0~5V
Minimum voltage range: -1V~1V Minimum voltage range: 0~5V
Digital I/O
Number of channels: 12 channels of bidirectional channels
Input current: leakage current, source current
Output current: leakage current, source current
Maximum voltage range: 0~5V
Minimum voltage range: 0~5V

According to the characteristics of the acquisition card, the acquisition frequency of the acquisition card is 48kS/s, and the acquisition speed is very fast. In the system designed in this paper, such a fast acquisition rate is not needed. In order to apply the acquisition card to the system well, we Made the corresponding changes. The average walking speed of the human body is about 0.5s, so the acquisition rate of the acquisition card is set to 1kS/s. Since the signal will be slightly fluctuated with the jitter of the static torque sensor, in order to solve the problem, make the data smoother and ensure the stability of the data, we need to eliminate the maximum value and the minimum value of the data in the local time period. Operation. In the filtering method adopted in this paper, based on the set acquisition rate, the data collected in the local time period is averaged, and the corresponding average value is taken as one sample data collected.

3.3. System Software Design

The system uses the NI USB-6009 Multifunction Capture Card for sample collection, and its manufacturer, NI, offers a complete NI software development platform that integrates with Measurement Studio for Visual Studio.net, LabView, and LabWindows. The software development of this paper is based on the NI software development platform and is programmed with Visual Studio2010 tools.

After the software is turned on, the program receives the data collected by the multi-function acquisition card through the serial port communication; in the initial process, the model initialization is performed according to the collected partial data, and the model order is mainly determined, and the window size is moved. This process is the learning and modeling process and is the core of the process. In order to enable the program to implement modeling faster, our prediction model provides an initialization step in the process of algorithm analysis and research. Only the order correction can be performed in the program, which greatly reduces the modeling. Time spent. The analysis and research of the predictive model will be discussed in Chapter 4. After successful modeling based on historical sample data, the signal prediction work is entered. After the serial port accepts the new data, the program predicts according to the prediction algorithm designed in this paper. After the prediction is over, what we need to do is sample interpolation work, and interpolate according to the predicted value and the current actual sample value. The purpose is to achieve frequency multiplication, improve the sensor response frequency, and solve the purpose that the response frequency is lower than the human neural response frequency. This will be discussed in Chapter 5. Finally, the sliding window movement operation is performed, and the window is moved forward one step to fully prepare for the signal prediction at the next moment.

3.4. Perceptual System Analysis of Wearable Power Assisted Robot

3.4.1. Analysis of the Perception System

The wearable booster exoskeleton robot mainly analyzes and models the human body based on the historical motion information, predicts the motion intention of the next moment, and assists the human body's movement through the control device. How to obtain the motion information of the human body is an important basis for the system to make predictions. At present, the measurement method of human motion information generally includes image information acquisition, angle information collection, and force information collection. The image information collection and angle information collection methods belong to the category of kinematic parameter measurement, mainly considering its time characteristics, spatial characteristics and space-time characteristics, such asSpeed, acceleration, angular displacement, angular acceleration, etc. The force information acquisition method belongs to the dynamic parameter domain, that is, the measurement torque, the moment of inertia and other parameters.

(1) Image information collection technology. The positional information of time and space is the most basic way to describe the movement, and the movement of the human body is carried out in a certain time and space. By taking a picture of the movement of the human body, the action state at each moment is recorded as historical information, and information is analyzed and modeled, and the state of the next action is finally predicted. At present, sports biomechanics mainly uses stroboscopic cameras, three-dimensional tracking and other methods to obtain motion state data of the human body's attitude changes at various moments during the movement.

(2) Angle information collection technology. The most direct response of the human body during exercise is the angular change of the hip, knee and ankle joints. During walking, the legs are lifted, the knee joints and hip joints are bent forward, and the ankle joints are bent so that the soles of the feet remain parallel to the ground. During the landing process, the joints are reversed to complete one step. Therefore, obtaining the angle change information of the human body at various moments during the movement through the angle sensor is the simplest method of recording the motion state during the movement of the human body. The method of measuring is to fix the center of the angle sensor to the side of the joint on the side of the joint. The two arms of the angle meter are fixed on the two limbs connected to the joint. During the movement of the human body, the bending of the joint drives the angle meter to change the angle between the two arms, so that the output voltage signal of the angle meter changes, reflecting the motion state information of the person at various moments in the motion process.

(3) Force information collection technology. The movement of the human body is characterized by the force generated by the contraction and expansion of the muscles, and the movement of the legs is controlled. Therefore, the motion information of the human body can be obtained by detecting the force information during the movement of the human body. During the experiment, real-time detection of the force between the person and the ground and real-time detection of the force between the person and the exercise device are generally performed.

3.4.2. Analysis of Sensor Signal Characteristics

The system's human motion signal acquisition method uses angle information acquisition technology and uses a static torque force sensor. The static torque sensor is located on the side of the joint, and the two arms are fixed on the joints of the joints. The principle of the angle information acquisition and measurement described in the previous section is the same. First, a stable DC voltage is applied to the sensor. During the movement of the human body, the bending of the leg joints causes the torque sensor to produce a twist, and the voltage signals at both ends are changed to reflect the motion state information of the human body during the movement.

The movement of the human body is mainly divided into three types: fast, normal and slow walking. The signal generated by the normal walking in slow walking is basically the same. The difference is that the speed of the curve is slow, so this article only refers to the human body. Fast motion and normal motion are analyzed for both motion states and voltage signals.

4. Sensor Signal Real-Time Prediction Algorithm

4.1. Overview of Particle Filter Technology

The so-called particle filtering technique refers to finding a set of propagated random samples in a state space of the system in order to converge to the probability density function, using the sample average The approximate calculation, not the integral calculation, is the process of estimating the minimum variance of the system in this state obtained in this way. The resulting random samples are treated as "particles", and particle filtering is named after it. In the middle of the 20th century, particle filtering technology was applied in the field of statistics and theoretical physics. Ten years later, it appeared in the field of automation control; in the 1970s, it also developed. However, due to the particle degradation phenomenon in the particle filtering method (that is, the phenomenon of diversity loss due to multiple iterations of particles) and the problem of measurement constraints have not been solved, the particle filtering method has not received sufficient attention. Until Gordon and other experts and scholars proposed the bootstrap particle filter algorithm in 1993, the research of particle filter was once again highly praised by everyone. In this algorithm, Gordon introduces the idea of resampling to solve the problem of particle degradation over time. This algorithm lays the foundation for the subsequent development of particle filtering. In addition, the rapid development of electronic computers and the rapid enhancement of their computing power also provide objective conditions for the physical realization of particle filtering.

A new leap in particle filter development in 2000, when Doucet et al. proposed a new general description of particle filtering based on sequential importance sampling (SIS) based on previous research. The large number theorem, Monte Carlo method is used to calculate the multiple integral problem in Bayesian estimation. SIS technology is used to obtain a set of particles in the state space of the system, and a corresponding importance weight is assigned to these particles. The weighted summation formula calculates all the obtained particles to obtain an estimate of the state posterior probability density. All subsequent improved algorithms are based on this technique. Doucet et al. laid a solid foundation for the study of particle filtering.

4.1.1. Introduction to Particle Filtering Algorithm

The standard particle filtering algorithm can be summarized as follows:

(1) Initialization. A set of particle sets 01 {} iN ix in this state is generated by the prior probability 0() px , where N is the total number of particles and the sum of the weights of all particles is 1.

(2) Update the particle weight. At time t, the weight of the particle is updated by the following equation.

$$w_t^i = w_{t-1}^i p\left(z_t \middle| x_t^i\right) = w_{t-1}^i p_{e_t}\left(z_t - h\left(x_t^i\right)\right), i = 1,2 \dots \dots, N \quad (1)$$

And normalize the weights of all particles by the following formula

$$\widehat{w}_t^i = w_t^i / \sum_{i-1}^{N} w_t^i \quad (2)$$

Finally, we can get the least mean squared estimate of the unknown parameter at time t by the weighted summation operation on the particles.

$$x_t \approx \sum_{i-1}^{N} w_t^i x_t^i \quad (3)$$

(3) Resampling. Resampling is a technique used to solve the problem of particle degradation in particle filter algorithms. A new set of particles is obtained by resampling.

(4) Forecast. The initial empirical condition distribution is corrected by the obtained particle information, and the state equation is used to predict the next unknown parameter

(5) Update the time so that t=t+1, and then go to step (2).

4.1.2. Development and Application of Particle Filter Algorithm

The defect of particle filter algorithm is the occurrence of particle degradation phenomenon, which is solved by resampling technique. However, the disadvantage of resampling technique is that in particle concentration, the number of progeny particles generated by particles with larger weights gradually The increase, while the smaller weight of the particles are eliminated, the worst consideration is that the regenerated particle set is generated by a particle of maximum weight, which is called the "sample exhaustion" phenomenon. In order to ensure the diversity of particles, a variety of algorithms have been proposed, such as: resampling move algorithm; fission bootstrap particle filtering (FBPF).

In the process of locating and tracking the target, due to the complexity of the actual problem, most of the problems that need to be faced are nonlinear and non-Gaussian problems. In response to these problems, experts and scholars such as Gordon proposed to apply the particle filtering method to the pure angle tracking problem and obtain better tracking accuracy. Subsequent tracking of the target has led to many research results based on particle filtering: nonlinear filtering methods for pure angle tracking, group target tracking based on particle filtering, and so on. In the financial field, because many of its time series data can be reduced to fuzzy random time-varying systems, in recent years, particle filtering ideas have been applied to data analysis and modeling research in this field.

Because the MAWDAR model is more self-regressive than the AR model, it also performs regression operation on the quadratic value of the sample, with high precision and simple operation. However, there are still large errors in a certain atmosphere.

4.2. Sensor Time Series Signal Optimization Algorithm

4.2.1. Introduction to the Eviews Tool

Eviews (Econometric Views) is a software developed by the US quality management system QMS Company (Quantitative Micro Software Co) for econometric analysis statistics. Its predecessor is the measurement software TSP, which is very good for data analysis, regression research and prediction. tool. The basic data objects processed by Eviews are time series, and the management and processing of cross-section data and panel data are also very convenient. It also has powerful command functions and rich program processing statements. It is widely used in economics, social sciences and other fields, and the software operation platform is the Windows platform.

The first time Eviews software entered China was in 1998, when the version was 3.1. Due to its good stability, it had considerable influence at the time, and Eviews version 3.1 was also hailed as the most classic version. Subsequent Eviews have been updated multiple times in 4.0, 5.0 and 5.1, and the latest version is version 6.0. The main advantage of Eviews software is that it does not require most of the learning time. Unlike some other econometric software, users need to spend a lot of time to learn the complex imperative language. Eviews' operation interface is a visual interface, mainly The mouse clicks on the driver and provides most of the tools that are often used in practice, such as ADF inspection tools, autocorrelation and partial autocorrelation functions.

4.2.2. Analysis of Correlation of Observations

The third chapter has analyzed the characteristics of the voltage signal curve collected by the static torque sensor. Here we use the Eviews 6.0 tool to observe the stability of the observation [38] and correlation analysis.

First, what we need to do is to judge the stationarity of the observations. The method used is the Augmented Dickey-Fuller (ADF). The ADF test is based on the Dickey-Fuller test method. The Eviews tool performs the time series data stationarity determination operation. The test steps are as follows:

(1) To test the original time series data, first select the first item as Augmented Dickey-Fuller, the second item as level, and the third item as None, and check the result. If the stationarity test is not passed, It is considered that the original time series data is not stable, turn (2).

(2) Set the third option to intercept and the second option to 1st difference for verification. Here 1st difference means that the data is subjected to a differential operation. If the test passes, the data after one difference is smooth, otherwise the second differential operation is performed.

(3) The test of the second difference sequence, the third item needs to be set to Trend and intercept while the second option is set to 2nd difference. According to historical experience, after the secondary differential operation is generally performed, the sequence is stable.

4.2.3. Basic Model Order Estimation and Short-term Window Size Determination

The main problem of the sliding window quadratic autoregressive model is the estimation of the model order and the estimation of the short-term window size.

From the above model, we can find that it is similar to the AR model, so here we use the AR model's fixed-order method to initially estimate the order of the model, then carry out the up-and-down floating verification around the initially determined order, and finally determine its order. . Since there are one term and quadratic term in the model, the way we choose is to analyze the correlation of the primary item data and its quadratic data separately.

For the MWDAR model, choosing the appropriate m, p, and q can improve accuracy. The choice of p and q should follow the following rules: (1) In order to improve the robustness of the model parameter estimation, the selection of p and q should not be too large; (2) according to the general empirical principle, the order q of the quadratic term should be less than Or equal to the value of p. Based on all the above analysis, the order selection for the MWDAR model is tentatively set to 5.

The choice of model short-time window is mainly the choice of the type of window function and the size of the window. In the signal processing process, in order to analyze the characteristics of the signal, it is common practice to take a part of the time segment for analysis, and then extend the signal time segment according to the cycle. When intercepting an infinitely constant signal, the signal spectrum is distorted, that is, a so-called spectral energy leakage problem occurs. In order to reduce leakage, different interception functions are generally used to intercept the signals, and these intercept functions are window functions, referred to as windows. The window functions currently used are: power window, using power functions on time variables, such as moment window, triangular window, etc.; trigonometric function window, using applied trigonometric functions, such as Haiming window, Hanning window, etc.; exponential window, Use an exponential function about variables, such as Gaussian windows.

At present, rectangular windows are the most used type of window function, which has the advantage that the main lobe is more concentrated than other windows. After the signal uses a rectangular window, it usually appears as no window. Compared with other window functions, it can be found that the rectangular window is relatively easy to implement in the signal processing process. Therefore, in this system, we select a rectangular window.

The size of the window mainly depends on the main lobe and resolution of the signal spectrum, and the real-time processing of the system signal designed in this paper is based on the calculation amount of the prediction algorithm, and also needs to be based on the order of the prediction model. Determined, generally 2*mp, and m needs to be greater than the number of observations included in the one-stage period during signal fluctuation.

4.2.4. Improved Model Based on PF Optimization - PF_MWDAR

Through the discussion in the previous section, the order of the MWDAR model and the window function and size of the short-term window are determined. Next, this paper will introduce the improved MWDAR model based on PF optimization. This model is called the PF_MWDAR model.

Assume that the time series is { | 1,2 }, m is the current time. According to the MWDAR model modeling idea, the autocorrelation coefficient is calculated for the time series and the ADF test is performed to determine that it is a non-stationary sequence. If not, the difference operation is continued and the stationarity is continued until it is a stationary sequence. Then the model order is estimated and the window size is determined. Finally, the initial prediction equation is obtained.

$$x_{m+l} \approx x_m(l) = \sum_{i=1}^{P} w_i x_{m+l-i} + \sum_{j=1}^{q} v_i x_{m+l-j}^2 \quad (4)$$

Where, ml x , () m xl are the true and predicted values of ml respectively; mlixip is historical or predictive data; where p and q are primary and second respectively The order of the second term, and pq ; { | 1,2 } iwip, , and { | 1,2 } jvjq, are the model coefficients of the primary and quadratic terms respectively obtained.

At time m, if you need to predict the advance (2) step, the usual method is to predict the advanced step first, then the advanced one-step prediction as the known observation value for the advanced two-step prediction, and so on, and finally Advance l step prediction. From the above explanation, it can be clearly found that when the model is not accurate enough, after the multi-step iterative prediction calculation of the model, the previous model prediction error will be brought in, thereby expanding the error and causing the advanced multi-step. The accuracy of prediction is declining. To this end, this article sets the next forecast to a simple one-step forecast to ensure its accuracy; at the same time, the PF optimization is modified on this basis.

Since the particle filtering method implements recursive Bayesian filtering by non-parametric Monte Carlo simulation, a set of particle sets is obtained based on the prior probability density, which is corrected by adjusting each particle in the particle set. The original state value, and when the number of particles reaches a certain number, the particle estimate is equivalent to the posterior probability density. Therefore, the PF optimization algorithm designed in this paper always uses the MWDAR model as the state transition equation of particles. The model parameters obtained by the model at each moment, that is, the model coefficients at time m are used as the prior probability of the Bayesian estimation of particle filter. Therefore, it does not produce distortion except for additive white Gaussian noise, and is the most basic interference and noise model in signal processing. A disturbance is added to each model parameter by this function, and the added noise signal-to-noise ratio is expressed in dB. Based on the probability density distribution after the disturbance, a set of particle sets is obtained, so that a corresponding set of particle filtering states can be obtained. Transfer equations, through these state transfer equations, we can get the posterior probability reference distribution.

Then we need to assign corresponding weights to each particle. The determination of the weight depends on the error between the fitted and actual values of the fitting moment. It is assumed that the true and fitting values at time m are mx and ˆm x , respectively. Then the weight is estimated as

$$d_m^l = |\hat{x} - x_m| \quad (5)$$

Where i md represents the weight estimate of the ith particle at time m.

In order to give higher weights to the calculated state estimation values that are closer to the true value, all the weights of the particles at a certain moment are calculated using a Gaussian function:

$$w_m^i = \frac{1}{\sqrt{2\pi\sigma}} \exp\{-\frac{d_m^i}{2\sigma^2}\} \quad (6)$$

Where im w represents the weight of the ith particle at time m,

is a given constant. After the Gaussian distribution operation, what needs to be done is the weight normalization operation.

$$\widehat{w}_m^l = w_m^i / \sum_{i=1}^N w_m^i \quad (7)$$

Where N is the total number of particle sets, normalized weights

Since the particle filter optimization algorithm-PF optimization algorithm is based on the MWDAR model, if the model parameters obtained by the MWDAR model are not accurate enough, the particle set obtained by the jitter based on the prior probability may have a larger error. In order to avoid the influence of these large error particles, these particles need to be deleted, so that the prediction accuracy is increased. At the same time, due to the deletion of particles, it appears to be degraded. In order to avoid this problem, resampling technology is used to solve it. The specific steps are as follows:

(1) First, the system gives an entropy variable value Q through the rand() function. The total weight is disum. When filtering each particle, the disum is initialized to zero.

(2) Adding the weights of the particles in turn by the following formula (4.8), each time adding a weight of the particles, it is necessary to compare with the random variables generated in step (1). If it is larger than Q, then The particle weights are retained as a new particle store; if smaller than Q, continue with step (2) until the disum value is greater than Q or all particle weights are processed, no more than Q after processing Large, the predicted value obtained by the MWDAR model is stored as the most particles.

$$\text{disum} = \text{disum} + d_m^i (i = 1,2 \ldots, N) \quad (8)$$

(3) Repeat steps (1) and (2) until N particles are obtained.

(4) Performing the mean operation on the obtained particle set as a one-step operation at time m.

$$x_m(l) = \sum_{i-1}^N w_m^i / N \quad (9)$$

In the formula, (1) mx is expressed as the predicted value of the leading step at time m, and im x is expressed as the ith adjusted particle obtained at time m.

Through the above operation, we can retain the particles with larger weights, and replace the deleted particles with the predicted values obtained by the MWDAR model as their particles to avoid the phenomenon of particle filter degradation.

4.3. Simulation of Sensor Time Series Signal Prediction Algorithm

In the previous section, this paper introduced the PF optimization algorithm based on the MWDAR model, and the feasibility of the algorithm needs to be analyzed and verified. In this paper, the algorithm is simulated by MATLAB software, and its effectiveness is analyzed and verified. The simulation of the algorithm mainly uses the signal data collected by the human body's fast walking and the static torque sensor installed at the thigh and knee joint during normal or slow walking to study and verify the PF optimization algorithm involved in this paper. In order to make the superiority of the algorithm obvious, we compare the predicted value obtained by the MWDAR model with the predicted value obtained by the PF optimization algorithm, and further compare the error between the predicted value and the true value obtained by the two methods. Compare and analyze the results. Since the PF optimization algorithm is optimized based on the MWDAR model, if the multi-step prediction is advanced, a multi-step iterative prediction experiment is needed, and the iterative process will bring in the previous prediction error, so that the prediction accuracy is declining. After optimization by the PF algorithm, it is possible to further expand the error, so the following algorithm simulation is a step ahead prediction, which ensures the accuracy of the prediction.

4.3.1. Simulation of Sensor Time Series Signal Prediction Algorithm during Fast Walking

Through previous analysis, the sensor's time series signal exhibits a shape resembling a sine or cosine curve during fast walking. In this paper, the number of samples collected by static torque force sensor is 126, the number of samples used for model learning modeling is 83, the number of samples for comparison observation is 43, and the number of particles in particle filter method is 200, disturbance signal noise The ratio is 30dB, and the prediction is a one-step prediction. The simulation results are shown in Figure 1. The circled line in the figure represents the raw data, the Mixing line represents the predicted value of the advanced one obtained by the MWDAR model, and the last line is the predicted value obtained by the PF-optimized prediction model PF_ MWDAR based on the MWDAR model.

From Figure, it is difficult to see the accuracy of the simulation results obtained by the two algorithms. In order to more accurately reflect the accuracy of the prediction of the two model algorithms, the actual sample values are compared with the predicted values. To calculate the prediction error, Figure shows the error analysis between the processed prediction signal and the original signal after the MWDAR model and the PF_MWDAR model prediction algorithm are used to predict the sensor time series signal during fast walking. From the figure, it can be clearly seen that the overall predicted value after optimization by the PF algorithm is more accurate than the predicted value obtained by the MWDAR model.

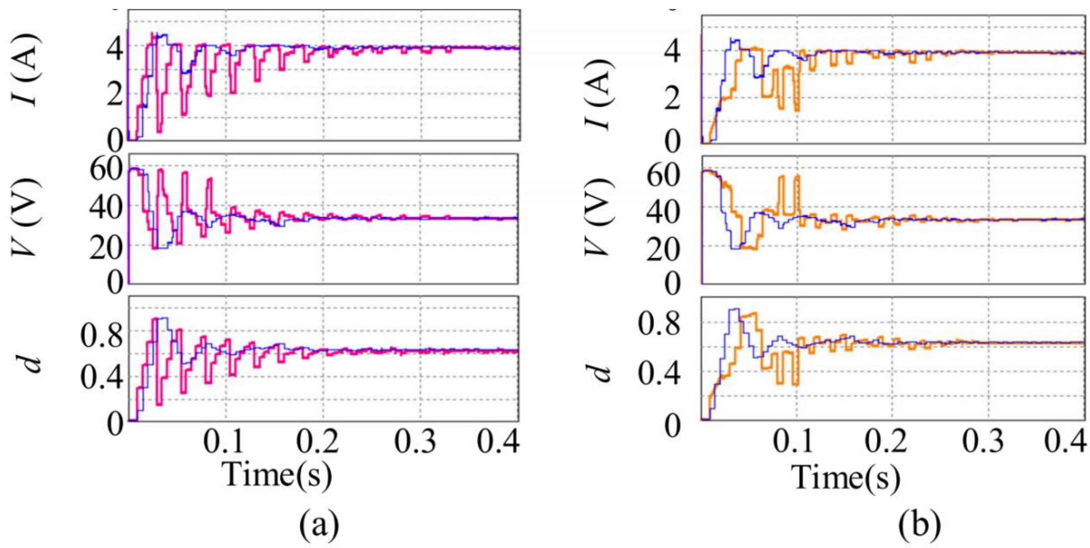

Figure 1. Simulation results

5. Conclusion

Under the increasingly serious reality of the aging population of the world, the research of wearable exoskeletons to help robots is of great significance. In the elderly because of their own physical ability, it can effectively help the elderly to walk normally, and can even be used to help people with disabilities with lower limbs to walk daily. The exoskeleton assisting robot mainly detects the movement state information of the human walking through the system perception system, and performs model fitting according to the historical information. Finally, the prediction algorithm is used to predict the movement intention of the next person, thereby achieving the purpose of helping the person to walk. At present, the research on exoskeleton robots has been more and more, and its application range is wide, both military and civilian. In this paper, the prediction algorithm of exoskeleton robot is deeply studied. On the basis of this, the particle filter optimization algorithm is combined with the MWDAR model, and a new predictive optimization algorithm is proposed. This algorithm can effectively improve the prediction accuracy. At the same time, in order to solve the calculation delay of particle filter optimization, the frequency multiplication algorithm is added, which also solves the problem that the system adopts static torque sensor and its sensor signal response frequency is low. The main research contents of this thesis are as follows:

(1) Overview of time series analysis, the basic modeling methods of several commonly used stationary time series models are introduced, especially the order and parameter estimation methods of the existing models are described in detail.

(2) The basic platform built in this paper is introduced for the acquisition of sensor signals, which provides data support for the simulation of the prediction algorithm. At the same time, the characteristics of the collected sensor signals are analyzed.

(3) The basic concept, characteristics and development of the particle filter algorithm are introduced. The MWDAR model is also described. Based on this, the PF_MWDAR model designed in this paper is proposed. The model order and parameter estimation are described in detail around the model involved, and the preliminary order and the window size of the model are determined.

(4) According to the characteristics of the curves presented in the two human walking processes summarized in this paper, the designed algorithm is simulated to determine the effectiveness of the

algorithm. (5) Aiming at the delay of the particle filter algorithm and the low response frequency of the sensor signal, a method of interpolation multiplication is proposed. Firstly, several interpolation algorithms commonly used at present are introduced, and their advantages and disadvantages are analyzed. Finally, the cubic spline interpolation algorithm is used, and then the simulation execution steps are designed. The multiplication algorithm is simulated by MATLAB software to verify the effectiveness of the algorithm.

Through theoretical derivation and simulation verification of the algorithm, the MWDAR-based PF optimization model designed in this paper can effectively improve the prediction accuracy. At the same time, the cubic spline interpolation algorithm is used to homogenize the interpolation, which effectively solves the large amount of calculation due to particle filtering. Delay and the low response frequency of the sensor signal.

Funding

This article is not supported by any foundation.

Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

References

[1] Y. Wen, Ping Li, Jin Yang and Min Zheng, "Detecting and evaluating the signals of wirelessly interrogational passive SAW resonator sensors," in IEEE Sensors Journal, vol. 4, no. 6, pp. 828-836, Dec. 2004. DOI:10.1109/JSEN.2004.837493

[2] S. N. Daskalakis, G. Goussetis, S. D. Assimonis, M. M. Tentzeris and A. Georgiadis, "A uW Backscatter-Morse-Leaf Sensor for Low-Power Agricultural Wireless Sensor Networks," in IEEE Sensors Journal, vol. 18, no. 19, pp. 7889-7898, 1 Oct.1, 2018. DOI:10.1109/JSEN.2018.2861431

[3] R. Carlos et al., "Web-based sensor streaming wearable for respiratory monitoring applications," SENSORS, 2011 IEEE, Limerick, 2011, pp. 901-903. DOI:10.1109/ICSENS.2011.6127168

[4] M. Abu-Saude and B. I. Morshed, "Accessing Differential Measures with a Conjugate Coil-Pair for Wireless Resistive Analog Passive (WRAP) ECG Sensors," 2018 IEEE International Conference on Electro/Information Technology (EIT), Rochester, MI, 2018, pp. 0887-0891.

[5] S. G. Hong, N. S. Kim, C. S. Pyo and W. W. Kim, "Hybrid Sensor Module and Data Processing Using Low-Power Wakeup in WSN," 2010 Fourth International Conference on Sensor Technologies and Applications, Venice, 2010, pp. 191-195.

[6] R. Khorshidi, F. Shabaninia, M. Vaziri and S. Vadhva, "Kalman-Particle Filter Used for Particle Swarm Optimization of Economic Dispatch Problem," 2012 IEEE Global Humanitarian Technology Conference, Seattle, WA, 2012, pp. 220-223.

[7] M. Li, L. Yuan and W. Du, "Unscented Particle Filtering with Particle Swarm Optimization for

Estimating Nonlinear System," 2010 Third International Symposium on Electronic Commerce and Security, Guangzhou, 2010, pp. 79-83.

[8] J. Zhu, X. Wang and Q. Fang, "The Improved Particle Filter Algorithm Based on Weight Optimization," 2013 International Conference on Information Science and Cloud Computing Companion, Guangzhou, 2013, pp. 351-356.

[9] R. R. Manikandan, A. Kumar and B. Amrutur, "A Digital Frequency Multiplication Technique for Energy Efficient Transmitters," in IEEE Transactions on Very Large Scale Integration (VLSI) Systems, vol. 23, no. 4, pp. 781-785, April 2015. DOI:10.1109/TVLSI.2014.2315232

[10] S. Ok, K. Chung, J. Koo and C. Kim, "An Antiharmonic, Programmable, DLL-Based Frequency Multiplier for Dynamic Frequency Scaling," in IEEE Transactions on Very Large Scale Integration (VLSI) Systems, vol. 18, no. 7, pp. 1130-1134, July 2010.