J. Electrical Systems 20-3 (2024): 841-851

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Application of Posture Recognition Model Based on Improved CORDIC Algorithm in Spatial Health Monitoring of the Elderly Living Alone

Abstract: - In an aging society, accidental falls are highly likely to occur due to external factors or the incidence of diseases in the elderly. Serious consequences can arise when an elderly person living alone falls and is unable to get up to call for help. To address the issue of automatic assistance for elderly individuals living alone when they fall by accident, and the problem of behavioral analysis in daily life, this paper designs and develops an elderly monitoring system through the study of feature extraction algorithms and posture recognition algorithms. Furthermore, this paper has also developed a set of three-dimensional spatial angle calculation methods suitable for implementation on a microcontroller. The CORDIC algorithm can compute two-dimensional spatial angles through simple addition, subtraction, and bit shifting operations. Through careful study of the CORDIC algorithm, it was found that applying the CORDIC algorithm twice can achieve the calculation of three-dimensional spatial angles. Through experimental testing, we can see that the algorithms proposed in this paper have achieved good experimental results in terms of computational accuracy and operation time, reaching a relatively advanced level.

Keywords: Accidental falls, Posture recognition, CORDIC algorithm, Health monitoring

I. INTRODUCTION

The fast advancement of science and technology in recent years has brought about a sea change in people's lives. One notable change is the ageing population, which has heightened people's interest in medical technology. Science and technology have traditionally been propelled forward by the desire to better the lives of humans. The pursuit of a more convenient and comfortable home is an eternal human desire [1]. A population's average lifespan is proportionate to its production. An ever-increasing average life duration is a direct result of the seemingly endless rise in productivity. Furthermore, more and more older people are living alone because their offspring want to live away from them, which is a direct consequence of the changing attitudes and lifestyles of people today [2]. As we become older, our bodies' internal architecture changes, our physiological functions deteriorate, and our capacity to react independently weakens. Getting up and calling for assistance after an unintentional fall may be a challenge for the elderly, whether it's due to their own health or other forces. As a normal part of becoming older, many otherwise healthy middle-aged and elderly persons can develop chronic conditions or unexpected illnesses [3]. Damage will be done if they are not attended to or reminded in a timely manner. More and more individuals are concerned about their health these days, thanks to advancements in science and technology as well as the expansion of social economies. Numerous medical professionals and family nursing workers are desperately needed by the rising number of empty nesters [4]. Therefore, in light of the growing number of empty-nest families, individuals should give some thought to how to address the issues of accident alleviation and health analysis for the elderly who live alone. Figure 1 shows the elderly's posture detection system that uses multi-sensor fusion.

Video surveillance technology is pervasive in our daily lives, but the old-school kind can only be used in two scenarios: first, when something out of the ordinary happens, the staff can review the footage to see if anything out of the ordinary is happening, and second, when something out of the ordinary happens, they can use it as evidence to treat the patient quickly [5]. But as human civilization progresses, people's demands for quality of life rise, people's activity spaces grow, and more and more events happen, making monitoring more and more challenging. The conventional method of depending on humans to view videos is ineffective since traditional monitoring technologies can't keep up with the demands of the present. One of the leading causes of unintentional injuries to the elderly is falling [6]. The ability for parents to remotely notify their children of impending dangers, such falls, should be a primary feature of any elderly monitoring system. Simultaneously, the system may capture the target's posture data in real-time for behaviour analysis down the road, and provide

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movement analysis of the target after some time has passed [7]. The elderly monitoring system's stated goal is to keep tabs on senior citizens in their homes via live video feeds; the system can then record and identify the seniors' posture or actions at a specific time in real-time, allowing for the assessment of whether or not the seniors have fallen and require immediate assistance. We can also determine whether the elderly are getting enough sleep or movement and provide advice on how to enhance their quality of life by looking at how long each posture of the monitored item lasted. Along with words, individuals often employ a variety of gestures to communicate with one another in everyday interactions [8-10]. People may learn important characteristics from visual data, such how to connect with eyes, gestures, and facial expressions. These visual cues may reveal the other person's true mood and possible intentions. Understanding the significance of human behaviours via computer processing is the pinnacle of computer vision research. An intelligent conference room, smart house, intelligent security system, etc. are just a few examples of the many applications of behaviour understanding.

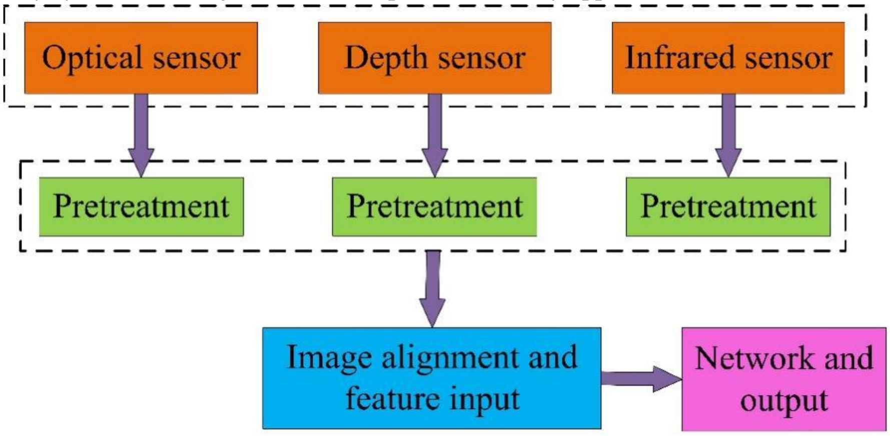

Figure 1: The Posture Recognition of the Elderly Based on Multi-Sensor Fusion

The main contributions of this paper are as follows. Firstly, we analyze that in the face of such a large elderly population and numerous difficult chronic diseases of the elderly, it is very unrealistic to implement one-to-one daily care. The study of this topic can support this work to a great extent by improving the quality of life of the elderly, preventing some chronic diseases of the elderly, and cooperating with the treatment of the diseases that have emerged to plague the lives of the elderly. In this paper, a three-dimensional spatial angle calculation method suitable for implementation on a single-chip microcomputer is developed. the CORDIC algorithm can calculate a two-dimensional spatial angle by simple addition, subtraction and shift operations. After a careful study of the CORDIC algorithm, it is found that applying the CORDIC algorithm twice can realize the calculation of a three-dimensional spatial angle. Through experimental tests, the algorithm proposed in this paper has good experimental results in terms of computational accuracy and operation time.

II. Related work

A. Current Situation and Trend of Behavior Recognition

Behavior recognition can be divided into lower-level gesture recognition and upper-level behavior intention recognition. The lower layer refers to the process of classifying which candidate action the action belongs to by extracting the characteristic parameters of the action [11]. The upper layer refers to the process that which the computer can understand or speculate the intention of a behavior. Behavior recognition technology can be divided into two types according to the way of collecting raw data: nonvisual sensor data collection and visual sensor data collection. The non-vision-based method is to collect the motion information of the target through wearable sensors or sensors fixed in the activity place [12]. The advantages of the above method are that the collected data is accurate, the interference factor is small, and the original data can be used for later pattern recognition only by simple processing. However, the disadvantage of this method is that it is invasive. Ordinary people do not need to wear sensors in their daily life. This will cause psychological and action burdens on the elderly in particular, and destroy the user's feelings [13]. Therefore, although the method based on non-visual sensors is relatively simple in technical implementation, its application field is limited, resulting in no significant development. Therefore, more and more research has begun to turn to the method of obtaining human motion characteristic parameters based on nonwearable sensors such as vision.

The rise of computer science and machine learning has piqued the interest of several prominent academic institutions and researchers in the field of behaviour analysis based on vision [14]. Future urban and battlefield surveillance systems may benefit from the system's automated video interpretation capabilities. Unsupervised intelligent monitoring, made possible by this project's use of image processing and pattern recognition algorithms, may detect potentially dangerous actions taken by the monitored item in real-time and alert the user accordingly [15]. By analysing the area under surveillance, the device may detect any concealed threats and relay that data over the network, allowing for remote monitoring. Both basic action identification at a low level and complicated behaviour comprehension at a high level constitute the study directions of behaviour recognition. Understanding complicated behaviour relies on effective simple recognition, which has received greater attention from bottom-up research [16]. Furthermore, there are two main schools of thought when it comes to visual representations of motion characteristics: those that rely on three-dimensional features and those that rely on two-dimensional features. One example is the need for a networked visual surveillance system for action recognition using 3D characteristics. In order to extract characteristics that are 3D view invariant, 3D reconstruction is performed using several cameras [17]. 3D models are better at representing people's everyday lives, but they come with a slew of drawbacks, such as sophisticated training and reconstruction algorithms, massive amounts of computation, and many distinctive parameters. The two-dimensional feature computation, on the other hand, is easy to understand and has seen extensive use. Distributed cameras allow us to overcome the challenges of changing angles and object occlusion, which arise when working with a single camera viewpoint. Figure 2 shows the present state and trend of behaviour recognition.

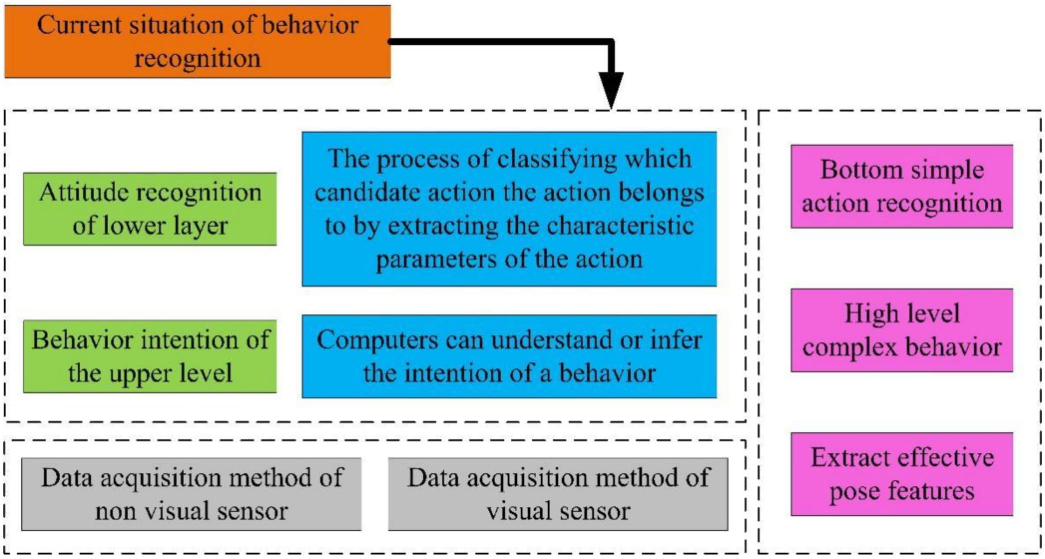

Figure 2: The Current Situation and Trend of Behavior Recognition

The above has introduced the application of behavior recognition in real life. Next, we will briefly introduce the related technologies used in the middle and lower level of vision-based behavior recognition. The lower level of action recognition should solve how to extract effective posture features and how to apply pattern recognition algorithms to action recognition [18]. This mainly involves the detection of human targets, the extraction of feature parameters, and the classification and recognition of actions. The original image data obtained by the camera includes moving targets and the surrounding environment. The process of finding out which pixels in the original image are moving targets is called target detection. Among them, we call the moving human target we are interested in the foreground and the surrounding environment as the background.

B. *Current Situation of Feature Extraction*

With the coming of the age of aging and fewer children, the guardianship of the elderly has become more and more prominent. Due to the long-term implementation of family planning policy in China, the elderly have gradually become the focus of attention [19]. The living conditions of disabled old people are not optimistic. At present, the main way of providing for the aged in China is to provide for the aged at home. Before disability, the elderly still have the ability to take care of themselves in daily life and do not need the care of others [20]. They can barely continue to adapt to this way of providing for the aged. For the disabled elderly, the basic shopping, cooking, and laundry can't be completed, especially during the illness, life is completely unable to take care of itself, and home-based care can't be achieved at all. In real life, there are even many sad cases in which the elderly died for many days before they were found.

There are unique qualities to every living organism in the natural world. A thing's traits are the telltale indicators that set it apart from similar objects [21]. In order to differentiate and identify objects, the human brain is able to parse their intricate representations for their distinctive characteristics. Consequently, we must also model this procedure when we want to employ computers as data processing tools to identify the actions and positions of a target. In order to facilitate the extraction of various foreground targets, researchers categorise the traits as either local or global [22]. One example is the global features, which are quite picky about the accuracy and completeness of the foreground target recognition findings. However, foreground target identification findings are inherently incomplete or erroneous in real-world applications owing to factors such as relative location, light variations, complicated backgrounds with several layers, target occlusion, and so on [23]. Local features have been extensively studied in academia and found widespread usage in real-time processing systems because to their insensitivity to foreground target identification results, ability to represent object effective information, and benefit of using less data. Full research on the feature extraction method for target recognition has not yet resolved all issues with its practical implementation. A critical issue, therefore, is how to acquire the best possible recognition results from the target recognition system by choosing the right characteristics for its many functions [24]. Various factors, such as the current scene, the characteristics of the target's movements, the pattern recognition algorithm, etc., form the foundation of feature selection. There is a lot of data in the picture format, and it takes a lot of computing power to extract complicated features. Although multi-feature fusion algorithms are sometimes required, improved real-time efficiency is essential for practical applications. The question then becomes how to strike a balance between speed and precision. Figure 3 illustrates the present state of feature extraction as well as its idea.

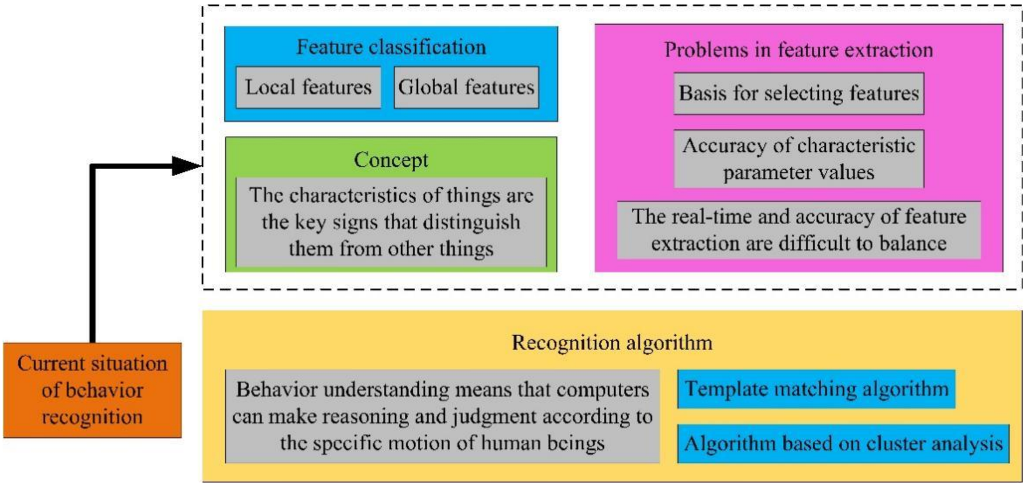

Figure 3: The Concept and Current Situation of Feature Extraction

Target recognition is a part of behavior understanding, which means that the computer can infer and judge according to the specific motion of human beings, and then give the results that human beings can directly understand. In intelligent video surveillance, automatic analysis and understanding of target behavior is the ultimate goal [25]. Good recognition results are the key guarantee for behavior analysis. From the perspective of the functionality of behavior detection, recognition algorithms include two categories: Algorithms Based on template matching and algorithms based on cluster analysis. Template matching algorithm refers to comparing the feature parameters extracted from the input image in the test stage with the feature parameters extracted in advance in the training stage, then the category represented by the known template most similar to the test stage is the recognition result of the image to be tested [26]. The algorithm of clustering analysis refers to dividing the input image sequence in the test phase into segments according to the set number of frames, extracting the feature vector of each segment, and then using the clustering algorithm, defining the segments with more categories as normal behavior, and defining the segments with fewer categories as abnormal behavior.

C. Sensor-based Attitude Recognition

At present, the research on attitude monitoring mainly focuses on two directions. Using iconology or MEMS to analyze attitude will inevitably use image acquisition equipment in the process of collecting raw data, such as cameras and video cameras, which is not in line with the original design intention of this topic for daily use. Therefore, this topic will focus on MEMS [27]. At present, in the relevant research on human posture monitoring and fall monitoring, most researchers use acceleration sensors combined with gyroscopes to measure. The acceleration sensor can measure the linear acceleration of the object by measuring the acceleration on the three-dimensional coordinate axis. However, the acceleration sensor can not measure the change of instantaneous rotation angle and rotation speed. The gyroscope positron makes up for this defect [28]. Therefore, in order to make an accurate measurement in the full six degrees of freedom space, it is necessary to attach the accelerometer and gyroscope to the limbs and trunk of the human body. However, the three-axis gyroscope still needs to be improved in terms of volume and power consumption. Therefore, multiple acceleration sensors and gyroscope units are installed on the human body to obtain the change information of each part in space and then judge or calculate the posture, position, moving distance, and action of the human body [29]. It also becomes impractical due to factors such as volume, processing and transmission of a large amount of raw data, and power consumption.

In terms of emergency monitoring, we are committed to real-time monitoring. Analyzing the balance of the body under static and dynamic conditions, giving an early warning for falls, and giving timely alarm after falls will be conducive to the rehabilitation of high-risk elderly patients after falls and injuries [30]. At present, the research on fall warnings is not very mature. In the study, the author analyzed the risk assessment of falls caused by several specified actions through the measurement of acceleration sensors in the environment of daily life and defined the risk factors. However, this study only uses one sensor, so the risk assessment is only applicable to several specified actions, and it can't deal with all the situations in daily life. The systems for fall detection can be roughly divided into two categories: image judgment and human body sensor networks [31]. The method of image judgment relies on the camera to directly transmit the human behavior to the telemedicine center through the image to achieve the purpose of monitoring or judging, and processing the collected image in the way of image processing, and reporting the identified dangerous situation to the telemedicine center through the network. However, due to the location and angle of the camera, the feasibility of this scheme has brought great limitations. At the same time, due to the problems of personal privacy involved in photographic monitoring, the current application of image discrimination to posture monitoring and fall detection is rare and impractical.

III. Design of Application Model

The CORDIC algorithm is an abbreviation for "coordinate rotation digital computer," which is the full name of the method. Its goal is to simplify two-dimensional operations in order to swiftly resolve real-time calculation issues in navigation systems using functions like square root, inverse trigonometric function, trigonometric function, and so on. While not the quickest, the CORDIC algorithm has the benefit of easy hardware implementation due to its reliance on just three operations: shift, addition, and subtraction. The following two modes of equations are often solved using the CORDIC algorithm: coordinate rotation mode and the other is as follows.

$$\mathrm{Y}' = \mathrm{K}(\mathrm{Y}\cos\lambda + \mathrm{X}\sin\lambda) \tag{1}$$

$$\mathrm{X}' = \mathrm{K}(\mathrm{X}\cos\lambda - \mathrm{Y}\sin\lambda) \tag{2}$$

Vector rotation mode is as follows.

$$R = K\sqrt{X^2 + Y^2} \tag{3}$$

$$\theta = \tan^{-1}\frac{Y}{X} \tag{4}$$

Let the rotation angle of each stage be α_i, the mathematical expression is as follows.

$$Y_2 = \pm X_1 = R_1 \sin(\theta_1 \pm 90°) \tag{5}$$

$$X_2 = \mp Y_1 = R_1 \cos(\theta_1 \mp 90°) \tag{6}$$

It should be noted that in the CORDIC algorithm, the vector is not the rotation of equal modulus, that is, R_i will change.

$$Y_{i+1} = \sqrt{1 + 2^{-2(i-2)}}R_i \sin(\theta_i + \sigma_i\alpha_i) = Y_i + \sigma_i 2^{-(i-2)}X_i \tag{7}$$

$$X_{i+1} = \sqrt{1 + 2^{-2(i-2)}}R_i \cos(\theta_i + \sigma_i\alpha_i) = X_i - \sigma_i 2^{-(i-2)}Y_i \tag{8}$$

After N-level rotation, the coordinate expression of the vector is as follows.

$$\mathrm{K} = \prod_{\mathrm{i}=1}^{\mathrm{n}} \mathrm{K_i} = \prod_{\mathrm{i}=1}^{\mathrm{n}} \sqrt{1 + 2^{-2(\mathrm{i}-2)}} \tag{9}$$

The mathematical expression after transformation is as follows.

$$\mathrm{Y_{n+1}} = \mathrm{KR_1}\sin(\theta_1 + \lambda) \tag{10}$$

$$\mathrm{X_{n+1}} = \mathrm{KR_1}\cos(\theta_i + \lambda) \tag{11}$$

The rotation of coordinates in linear mode, circular mode, or hyperbolic mode is unified into the same CORDIC iterative equation, which provides the premise for the same hardware to realize multiple functions. The iterative equation is as follows:

$$X_{n+1} = X_n - m\sigma_n Y_n \cdot 2^{-n} \quad (12)$$
$$Y_{n+1} = Y_n + m\sigma_n X_n \cdot 2^{-n} \quad (13)$$
$$Z_{n+1} = Z_n - \sigma_n \theta_n \quad (14)$$

Because the structure of the CORDIC iteration unit in each stage is the same, it is easy to implement with pipeline structure. The realization of an efficient pipeline structure depends on the minimization of the rotation path. Since then, the CORDIC algorithm with pipelined structure has been widely used in sine wave generators, fixed or adaptive filters, discrete orthogonal transform, and signal processing. The shift of each stage is realized by the shifter corresponding to that stage, and the total number of shifts is determined by the stage of the pipeline. The shifter of each stage is connected with the adder of that stage. In this way, the shifter can be ignored in the pipeline structure. The delay of the algorithm mainly depends on the working time of the adder. Therefore, the traditional pipeline algorithm can not reduce the delay and has little room for development. The CORDIC has higher coding efficiency and better error performance. The corresponding pseudo rotation in level I rotation is defined by the following formula:

$$x_{i+1} = x_i - \left[\sigma_1(i)2^{-r_1(i)} + \sigma_2(i)2^{-r_2(i)}\right]y_i \quad (15)$$
$$y_{i+1} = y_i + \left[\sigma_1(i)2^{-r_1(i)} + \sigma_2(i)2^{-r_2(i)}\right]x_i \quad (16)$$

The pseudo rotation steering amount is obtained after rotation. According to the above formula, the mathematical expression of the scale factor is as follows.

$$\mathrm{K_i} = \left[1 + \left(\sigma_1(\mathrm{i})2^{-\mathrm{r_1(i)}} + \sigma_2(\mathrm{i})2^{-\mathrm{r_2(i)}}\right)^2\right]^{-1/2} \quad (17)$$

In order to obtain high accuracy, the improved algorithm is described as follows:

$$\tilde{\mathrm{x}}_{\mathrm{i}+1} = \tilde{\mathrm{x}}_{\mathrm{i}} + \left[\mathrm{k_1(i)}2^{-\mathrm{s_1(i)}} + \mathrm{k_2(i)}2^{-\mathrm{s_2(i)}}\right]\tilde{\mathrm{y}}_{\mathrm{i}} \quad (18)$$
$$\tilde{\mathrm{y}}_{\mathrm{i}+1} = \tilde{\mathrm{y}}_{\mathrm{i}} + \left[\mathrm{k_1(i)}2^{-\mathrm{s_1(i)}} + \mathrm{k_2(i)}2^{-\mathrm{s_2(i)}}\right]\tilde{\mathrm{x}}_{\mathrm{i}} \quad (19)$$

For the hybrid CORDIC algorithm, the rotation angle is decomposed into:

$$\theta = \theta_M + \theta_{\mathrm{L}} \quad (20)$$

Among them, θ_M represents the main part of the rotation angle, θ_{L} represents the small part of the rotation angle, which is respectively defined as:

$$\theta_{\mathrm{M}} = \sum_{\mathrm{i=1}}^{\mathrm{p-1}} \sigma_{\mathrm{i}} \tan^{-1} 2^{-\mathrm{i}} \quad (21)$$
$$\theta_{\mathrm{L}} = \sum_{\mathrm{i=p}}^{\mathrm{n-1}} \mathrm{d_i} 2^{-\mathrm{i}} \quad (22)$$

The coarse and fine rotating parts of hybrid CORDIC algorithm are implemented by cascading. As shown in Figure 4.

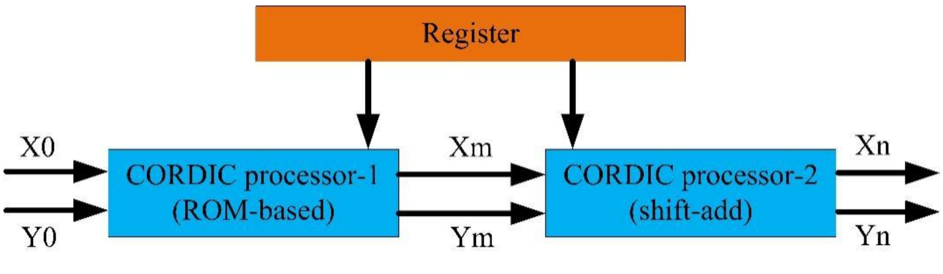

Figure 4: The Coarse and Fine Rotating Parts of the Hybrid CORDIC Algorithm

Firstly, complete the coarse rotation angle part in the processor and output an intermediate vector.

$$\begin{bmatrix} x_M \\ y_M \end{bmatrix} = \begin{bmatrix} 1 & -\tan\theta_M \\ \tan\theta_M & 1 \end{bmatrix} \begin{bmatrix} x_0 \\ y_0 \end{bmatrix} \quad (23)$$

The fine rotation angle part is completed in the processor, and the input end of the processor is connected with the output end of the processor. The final output vector is:

$$\begin{bmatrix} x_n \\ y_n \end{bmatrix} = \begin{bmatrix} 1 & -\tan\theta_L \\ \tan\theta_L & 1 \end{bmatrix} \begin{bmatrix} x_M \\ y_M \end{bmatrix} \quad (24)$$

IV. Overview of The Elderly Monitoring System

The four primary components of the system for recognising the behaviour of the elderly are a hardware module for video capture, a method for detecting human targets in the background, an extraction method for target feature parameters, and a recognition system for posture and action patterns. The first step is to employ a stationary camera to record video in real-time and then transform it into a computer-friendly picture format. After that, we acquire a picture with just human targets by doing image preprocessing and moving target detection. The next step is to deduce from human targets the defining characteristics that allow for posture differentiation. Last but not least, the classifier is either trained or recognised using the data and method associated with the distinctive parameters. Figure 5 depicts the whole system flow.

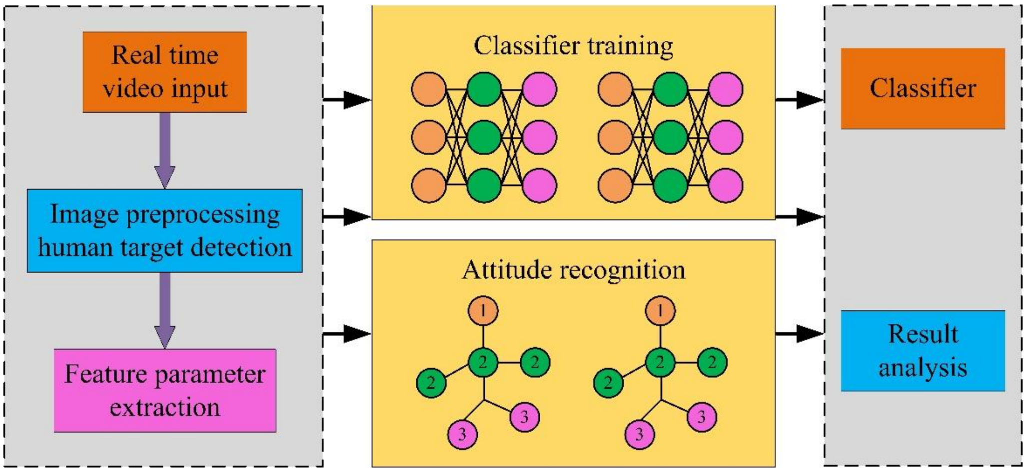

Figure 5: Working Process of the Elderly Monitoring System

After collecting real-time video, the typical first step is to separate the moving object from the video obtained by the fixed camera. The human brain can automatically process the visual information it sees, and distinguish which are moving objects or objects of interest, which are fixed environmental information or moving interference information. For a computer, an image is a two-dimensional matrix, the basic element of which is pixels, while a video is a series of images that are continuous in time. The classic algorithm of the foreground object detection algorithm is background subtraction, which subtracts the pixels of the current input frame image from the pixels at the same position in the reference background to determine whether it is foreground or background. However, the actual scene environment is often complex, and the surrounding environment will change. For example, with the change of time every day, the light will change, the weather will also change, and people or other animals may also change the environment and other interference factors, which makes the detection and extraction of foreground a challenging task. The effect of foreground target detection will have a great impact on the subsequent feature extraction and pose recognition of human targets. Because after the foreground detection phase is completed, we only do feature parameter extraction and pose recognition for the extracted foreground, human target detection is the basis for accurate feature parameter extraction and correct pose recognition. Researchers always tend to find a foreground detection algorithm that can meet all environments, but this is impossible to achieve. We should comprehensively consider the monitoring scenarios and system requirements to select and improve the foreground detection algorithm.

A real-time foreground segmentation algorithm based on improved two-layer codebook background modeling is used, which is a background model suitable for long sequences compressed according to the clustering algorithm. Although the environmental background in life is not static, the background information presents a kind of periodic movement for a long time, so it can be trained to get structured background information under the condition of limited storage space. The extraction of posture feature parameters is the second largest link in the elderly monitoring system, and it is also a very critical link. The feature extraction module has the function of connecting the past and the future. Its basis is the result of foreground detection, and the result of the feature extraction module is the input data of classification and recognition. The feature extraction module will have a great impact on the accuracy and real-time processing speed of the elderly posture recognition system. Feature extraction technology must complete two basic tasks: one is to convert images into numerical values, and these features can compress the feature dimension of things; Second, it can extract the characteristics that can best represent the thing from the appearance of the thing, that is, the characteristics that can distinguish the most from other things. Image feature extraction is a process of quantifying an image target with a set of feature parameter data, which realizes the transformation from image to value. The training process loss convergence curve and performance improvement are shown in Figure 6 and Figure 7.

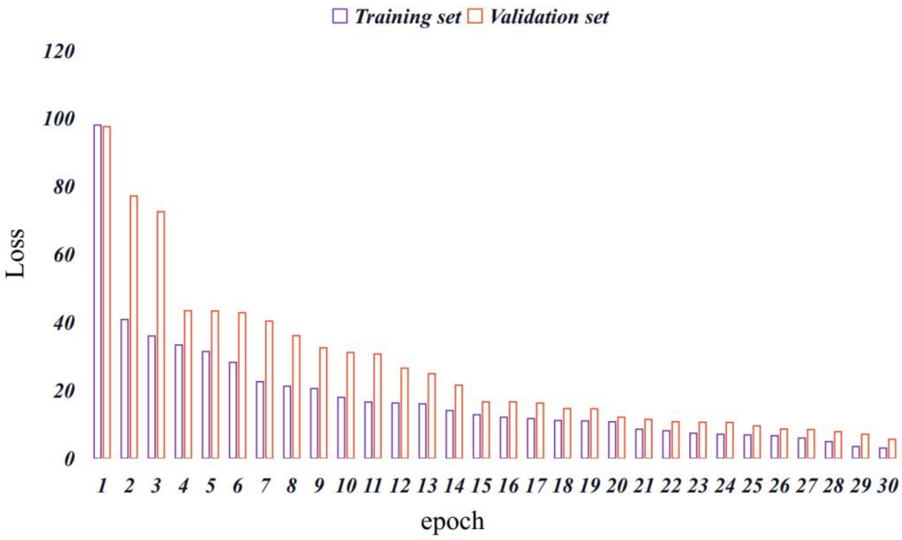

Figure 6: Training Process Loss Convergence Curve

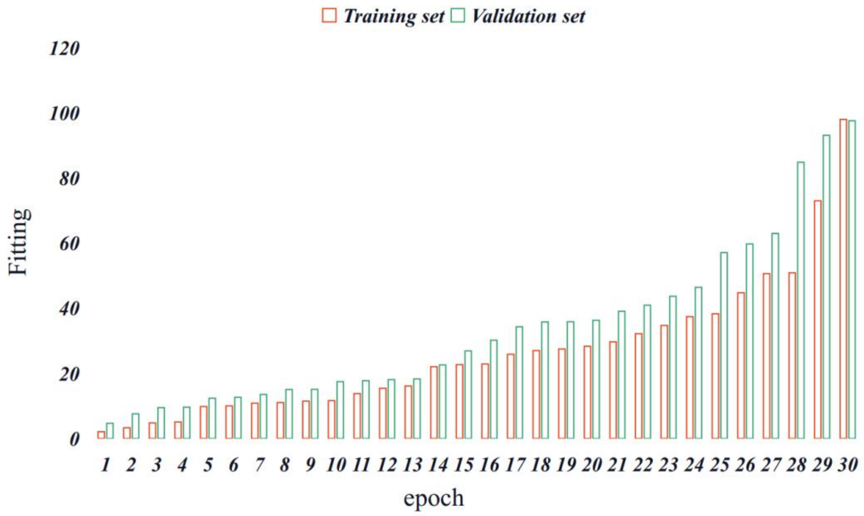

Figure 7: Training Process Performance Improvement Diagram

V. Experiments and Results

This study uses a behaviour analysis database for training and a self-made movie for recognition. Tables 1 and 2 as well as Figure 8 show the statistical recognition rate. This paper's experimental data comes from a domestic Chinese smart ageing company's internal, non-public data. Here are the model parameters: 256-dimensional feature vector, 0.005-second learning rate, 3, 4, and 5-window filter selection, 0.5-second dropout, and 128-batch size. In this self-recording video format, we see a single gesture performed by a single individual in a variety of contexts. Based on the outcomes, it is clear that this algorithm produces very effective and practically applicable recognition results. Since standing and sitting share certain traits at an angle, the recognition rate for both is somewhat low. A condition that is not clearly specified occurs when the sample that has to be classed differs from the established candidate category. Ubuntu 18.04, TensorFlow 1.14, Python 3.5, and an Intel i7 3.30 GHz processor with 256 GB of RAM and an Nvidia 2080TI graphics processing unit make up the experimental environment. Python 3.5 with TensorFlow 1.14.

Table 1: Recognition Rate of the Algorithm in the Behavior Analysis Database

	Stand	Bend	lie
Test set	98%	97%	100%
Validation set	95%	93%	99%

Table 2: Recognition rate of the algorithm in the self-made video library

	Stand	Bend	lie
Test set	97%	97%	95%
Validation set	95%	92%	94%

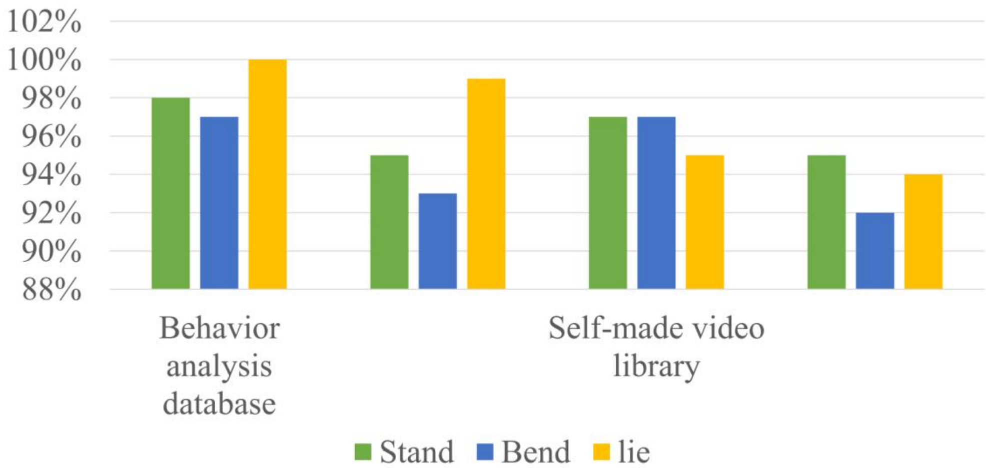

Figure 8: Recognition Rate of Our Algorithm

The training process of classifiers is as follows. First, according to experience, set the duration of action to about 60 frames. The selected samples are all 60-frame action videos, including upright walking, sitting down, lying down, and falling. The difference between the lying down video and the falling down video is that lying down is the conversion process from sitting posture to lying posture, and falling is the conversion process from standing posture to lying posture. The specifications of the video data used are 50 training videos and 40 test videos for each action. Each video contains only one continuous process of action, with a resolution of 352*288 and a frame rate of 21 FPS. The recognition results obtained from training and testing with self-recorded videos are shown in Table 3 and Figure 9. According to the results, we can see that the recognition results of simple actions are acceptable, and the occurrence of abnormal behaviors can be detected more accurately.

Table 3: Action Recognition Rate of this Model

	Walk	Sit down	lie	Fall
Test set	98%	97%	100%	95%
Validation set	95%	93%	99%	85%

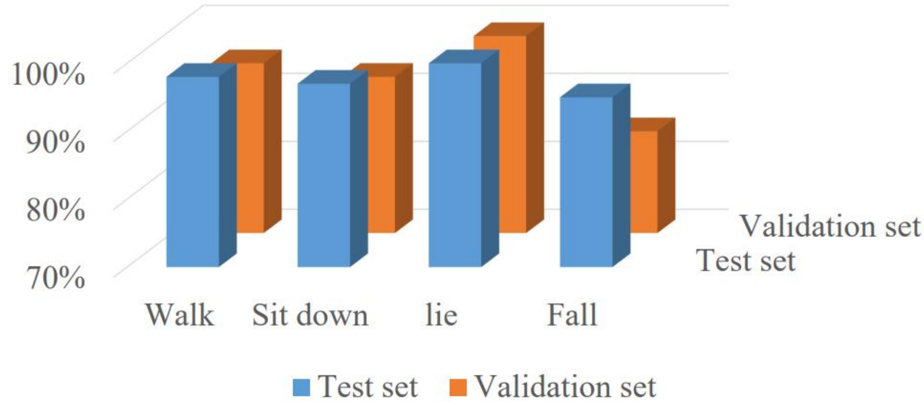

Figure 9: Action Recognition Rate of This Model

This chapter realizes the recognition of single-frame attitude and multi-frame action through two algorithms. Through the classification recognition algorithm, the single frame posture recognition of standing, sitting, bending, lying, etc. is realized. Through the designed attitude quantization algorithm and algorithm, the detection and recognition of multi frame actions such as walking, sitting, abnormal falling are realized.

VI. Conclusion

With the rapid development of science and technology, the progress of medical technology, and the family planning policy. Together, it is the trend of population aging in China in recent years. In the face of such a large group of elderly people, it is obviously impossible to achieve the health care of the elderly simply by manpower. It is undoubtedly an inevitable trend to rely on the power of science and technology to solve the above problems. In order to solve the problem of automatic help-seeking when the elderly living alone fall down accidentally and the problem of behavior analysis in daily life, this paper designs and develops the elderly monitoring system by studying the feature extraction algorithm and posture recognition algorithm. In addition, this paper develops an improved CORDIC algorithm which can calculate a two-dimensional space angle through simple addition and subtraction and shift operations.

Due to the limited time, and this topic involves the research and development of multiple platforms, it is inevitable that some details need to be improved. First of all, it can involve placing the main control module at the waist, and involving an acceleration sensor with the main control module, which can simplify the complexity of the whole system to a certain extent. Secondly, due to the limitations of the experimental environment, it is impossible to sew the wire in the clothes, and the instructions are attached to the limbs, which inevitably affects the experimental results. Finally, a total of 9 acceleration sensors are used in the undergraduate project. In actual use, the position and number of sensors can be adjusted according to different application scenarios. In the future, we plan to carry out the application of recurrent neural network-based posture recognition model in spatial health monitoring for elderly people living alone.

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