Hand Gesture Controlled Nursing Bed Using FMCW Radar

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Abstract. The nursing bed has become an important tool for medical and elder care, as a well-designed bed can prevent users from bedsores. To improve the user convenience, a user-friendly human-computer interface is also necessary. In this paper, we design a new nursing bed containing a FMCW millimeter wave radar for gesture recognition. A control system can help user frictionless back-up, integral turning over and leg raising when lying in the bed. Besides, we adopt the convolutional recurrent neural network for recognition of 6 gestures. Experiments with the nursing bed show that the control success rate of the bed reaches 93.75% and the response time achieves 1.03s.

1. Introduction
In recent years, China's population aging has developed rapidly. The number of elderly people aged 65 and above and their proportion in the total population have continued to increase. It is expected that China will enter an aging society in 2022. At the same time, the number of semi-disabled and disabled elderly in the elderly population continues to increase, bringing great pressure to home care [1]. Bedsores are one of the common complications of long-term bedridden patients, which may lead to prolonged disease treatment cycles, tissue infections and even death. Bedridden patients have a bedsore probability of 25-85%. The bedsore rate of elderly patients in nursing homes is 17.4%. The death rate of bedsores increases by 4 times, and the death rate of unhealed wounds is 6 times [2]. After the formation of bedsores, not only the quality of life of patients will be seriously reduced, but the family and society will also bear great pressure and burden.

Nursing beds are an important tool for elderly care and nursing care for disabled elderly people, and their main function is to prevent bedsores. It is difficult for the disabled elderly to change their posture autonomously when they are lying in bed, causing certain parts of the body to be squeezed for a long time, resulting in bedsores. The back of the head, back shoulders, waist, sitting bones, and back heels are common parts of bedsores. Posture changes can effectively prevent bedsores. Common postural changes such as raising back, turning over, and raising legs can be realized through nursing beds, which can improve pressure distribution and achieve the purpose of preventing bedsores.

The current nursing beds on the market have the following problems: (1) The function is single and cannot help the patient to complete a variety of posture adjustments; (2) The design does not conform to the ergonomics principle, and the product has low comfort during exercise; (3) The Human-Machine interaction is poor, the degree of automation is low, and it relies on manual control, which increases the workload of the nursing staff; (4) The friction and shear force during exercise are large, and it cannot play a good role in preventing bedsores [3].

In order to improve the usage convenience of the nursing bed, it is necessary to adopt the user-friendly human-computer interface (HCI). Because using human gestures can be a more natural way
of providing an interface between humans and computers [4], adding a radio sensor like millimeter wave (mmwave) radar for gesture recognition helps patients control the nursing bed much more easily, with just waving hands. And compared to vision, patients don’t need to turn on the lights at night when performing gestures using radar.

This article designs a new type of nursing bed for the elderly. The innovative mechanism realizes the frictionless back-up function and the integral turning function, which can prevent the occurrence of bedsores from the mechanism; the overall movement is ergonomic, natural and comfortable; the patient can perform gesture control by himself, reducing the workload of the nursing staff; the use of millimeter wave radar for gesture control can effectively protect the privacy of patients compared to vision.

The rest of the paper is organized as follows. Section 2 introduces three functions of the nursing bed. In Section 3, the control system of the nursing bed is described. Section 3 presents the method for gesture recognition based on the FMCW radar. In Section 4, we conduct the experiments and analyze the results. Finally, Section 5 comes to the conclusion.

2. Mechanical design

The functions of this nursing bed include frictionless back-up, integral turning over and leg raising. After analysing most of the nursing bed mechanisms on the market, we decided to adopt a rod mechanism with simple design, low cost and easy realization of required functions [5, 6].

2.1. Frictionless back-up function

The main cause of bedsores is that certain parts of the body have been compressed for a long time, blood circulation is blocked, and the compressed parts are always in a state of ischemia and hypoxia, metabolites cannot be discharged, resulting in tissue degeneration and necrosis. The forces that produce compression include vertical pressure, shearing force, and frictional force. The prone parts and directions of the force are shown in Figure 1 [7].

![Figure 1. Schematic diagram of compression force location and direction.](image)

The traditional back-up method directly adopts the fixed-axis rotation method, so that the stress point slides on the back, which will cause a lot of friction and cause secondary injury to the skin ulcer patient; and the buttocks are subjected to greater positive pressure during the back-up process. And the shearing force is not conducive to the prevention of bedsores; the whole back-up process is relatively rigid, which does not conform to the natural back-up method of the human body.

![Figure 2. Schematic diagram of the frictionless back-up function mechanism.](image)
Therefore, we designed a symmetrical sliding six-bar mechanism to couple multiple motion processes such as the back-side-panel flip, the head-panel up, the back-panel up, and the back-panel backward; and the force point is fixed, which is extremely reducing friction and is beneficial to the prevention of bedsores. The schematic diagram of the mechanism is shown in Figure 2.

The back-up process is shown in Figure 3. The sliding crossbar is used as the original moving part and moves on the moving pair, and the six-bar mechanism moves under the pushing of the original moving part. The back-up push rod pushes the back-side-panel to turn over to prevent the bedridden from sliding. The head-panel is slightly lifted under the drive of the back-side-panel flip, so that the head is stressed, which conforms to the natural way of lifting the back of the human body. When the back-side-panel and the head-panel move to the limit position, it cannot continue to move relative to the back-panel. Then, the back-panel is pushed up and slides backward at the same time. During the whole process, the stress point is fixed on the back, and the relative displacement between the bed panel is used to replace the sliding of the back of the person, so that there is no relative sliding between the back and the bed panel, and friction is reduced.

![Figure 3. Frictionless back-up process.](image)

2.2. Integral turning over function

The traditional turning over is only the upper half of the body, or the two-fold turning over is used, and the bed board directly rotates around the back axis. This way of turning over will not only squeeze the back of the shoulders and reduce comfort but also makes the sides without side-slip protection when turning over, which is easy to get injured. This article uses the three-fold turning over method shown in Figure 4 below to ensure that the patient can turn over as a whole, and at the same time have protection on both sides, which is safer.

![Figure 4. Turning over method](image)
The design of this paper realizes the function of integral turning over through the rotation of 4 turning-brackets and a combined hip-panel, as shown in Figure 5 below. Under the action of the electric push rod, the combined hip-panel rotates around the central axis, and the turning bracket is used as a follower to rotate accordingly. The bed board is a three-fold design, when one side is turned down, the other side is turned up, forming a "V" shape, which prevents the patient from sliding sideways during the process.

Figure 5. Turning over structure (a)Turning bracket. (b)Combined hip-panel.

2.3. Leg raising function

The schematic diagram of the leg-raising functional mechanism is shown in Figure 6. An electric push rod is used to achieve the up and down of the calf-panel, change the stress state of the foot, and reduce the probability of bedsores in the heel and ankle.

Figure 6. Schematic diagram of leg-raising functional mechanism.

3. Control system design

The core processor of this project is the Arduino UNO development board, which has fourteen digital I/O pins, six analog input pins, one 16 MHz crystal oscillator, etc. It contains everything the microcontroller needs. The interface meets the basic requirements, and the chip is reasonably priced and small enough to meet the needs.

The control system is shown in Figure 7. The gesture recognition algorithm is run by the computer, and the recognition result is sent to the Arduino through the serial port. The Arduino sends instructions to the motor driver to change the direction of the current and control the movement of the motor. We use DC drive motor in this project, which can realize the forward and reverse rotation of the motor by changing the direction of the current.
4. Gesture recognition based on mmwave radar

4.1. Related works
Recently, gesture recognition based on radar has become more and more popular. There are a lot of researches about gesture recognition based on the frequency-modulated-continuous-wave (FMCW) radar [8-13]. The authors in [12] investigated the effect of a training Convolution neural network (CNN) for millimeter-wave radar-based hand gesture recognition (MR-HGR) and proposed a parameterized representation of temporal space-velocity (TSV) spectrogram as an integrated data modality of gesture features in the radar echo signals. They evaluated models included ResNet, DenseNet, light-weight MobileNet V2 and ShuffleNet V2, and the cross-testing (CT) results indicated that the best fine-tuned models reached an average accuracy higher than 93%. The authors in [8] proposed a multi-modal cross learning approach to augment the neural network training phase. They used Range-Doppler maps, thermal camera images and RGB camera images for training the network, while only Range-Doppler maps were needed when recognizing gestures through the network. The multi-modal cross learning approach considerably outperformed single-modal approaches on challenging classification task. The authors in [11] built a real-time signal processing framework based on a 60 GHz FMCW radar and developed a hand activity detection (HAD) algorithm to detect the hand motion. Then they fed the hand profile detected by HAD into the CNN with low latency. As a result, the proposed framework archived a high F1-score of 94.17 when classifying 12 gestures in real-time.

4.2. Radar system
In the gesture recognition program, we use the FMCW radar provided by Infineon. The operating frequency of the radar is 60 GHz, and the maximum bandwidth is 5 GHz. Figure 8 shows the Infineon radar chip and baseboard. The radar chip has 1 transmit antenna and 3 receive antennas. The receive antennas are arranged in an L shape, so the radar can collect data containing angular information.
4.3. Signal Processing

The radar transmits signal and receives the signal which is reflected by the detected target. The waveform of the FMCW radar is shown in Figure 9. The transmitted signal (TX) is the sine wave with linearly increasing frequency. Theoretically, the shape of received signal (RX) is the same as the transmitted signal, while there is a time lag between the transmitted signal and the received signal. The time lag is caused by the distance between the radar and target. The radar mixes the TX and RX waves and output the intermediate-frequency signal (IF) $S_{IF}(t)$ as follows:

$$ S_{IF}(t) = A_{IF}\exp\{j[\psi(t) + \omega(t)t]\}, t_d < t < T_r $$  

$$ \omega(t) = 4\pi \frac{Kd(t)}{c} $$  

$$ \psi(t) = 4\pi \frac{d(t)}{\lambda} $$

where the $A_{IF}$, $\omega(t)$ and $\psi(t)$ are the amplitude, frequency and phase of the IF signal. $t_d$ is the time lag between TX and RX. $K$ is the increasing rate of frequency of TX which is set to $0.04$ GHz/µs. $T_r$ is the frequency increasing time which is set to $128$ µs. $c$ is the speed of light. $d(t)$ is the distance between the radar and target. $\lambda$ is the wavelength of the radar waveform and it is set to $5$ mm.

In theory, the IF signal is the sine wave with certain frequency and phase. The frequency and phase are related to range of target, and the phase change is caused by the relative velocity of target to the radar.

![Figure 9. FMCW waveform in frequency-time chart.](image)

The IF signal in the time period when the frequency of TX signal is increasing is called a chirp. When the radar is operating, it transfers data in the form of frames. Each frame contains dozens of chirps. We rearrange the data of each frame in the form of a two-dimensional matrix. Each row of the matrix represents one chirp, and chirps of the frame are listed in chronological order to form the matrix. We adopt 2D Fast Fourier Transform (2D FFT) to the matrix in order to extract frequency domain information which can be used for obtaining the range and speed of target. With 2D FFT, the output of frame $t$ called range-speed map is:

$$ C(p, q, t) = \sum_{m=1}^{N_{chirp}} \left( \sum_{n=1}^{N_{sample}} c(p, q, t) \exp \left( -j \cdot \frac{2\pi p n}{N_{sample}} \right) \right) \exp \left( -j \cdot \frac{2\pi q m}{N_{chirp}} \right) $$  

$$ RS(r, v, t) = |C(k_r p, k_v q, t)| $$

where $p$ and $q$ are range and speed index. The $N_{sample}$ is the number of samples in one chirp and it is set to 128. The $N_{chirp}$ is the number of chirps in one frame and it is set to 32. $c(p, q, t)$ and $C(p, q, t)$ represent the data matrix before and after 2D FFT respectively. $k_r$ and $k_v$ are ratios which convert range and speed index into value. $RS(r, v, t)$ is the range-speed map transformed from $C(p, q, t)$.

In addition, $k_r$ and $k_v$ can also be represented as the resolution of range and speed as follows:
\[ k_r = \frac{c}{2B} = 3 \text{ cm} \]  \hspace{1cm} (6)

\[ k_v = \frac{\lambda}{2N_{\text{chirp}}(T_r + \tau_{\text{delay}})} = 16 \text{ cm/s} \]  \hspace{1cm} (7)

where the \( c \) is the speed of light, and \( B \) is the bandwidth of TX which is 5 GHz. \( \lambda \) is the wavelength of the radar waveform and it is set to 5 mm. \( T_r \) is the frequency increasing time which is set to 128 \( \mu \text{s} \). \( \tau_{\text{delay}} \) is the time delay between the end of one chirp and the start of next chirp. The sum of \( T_r \) and \( \tau_{\text{delay}} \) is set to 505.64 \( \mu \text{s} \). The \( N_{\text{chirp}} \) is the number of chirps in one frame and it is set to 32. For the sake of gesture recognition in real time, we set the frame rate to 24 frames per second.

4.4. Gesture detection and classification based on CRNN

The procedure of gesture recognition is shown in Figure 10. When the mmwave radar is operating, we get 24 frames per second and process the signal in real time. Therefore, we gain three range-speed maps provided by three different antennas at the rate of 0.417 Hz. In order to recognize gestures, we develop the Convolutional Recurrent Neural Network (CRNN) to extracted to detect and classify gestures.

The CRNN structure is made up of convolution neural network and recurrent neural network, which is shown in Figure 11. Convolution neural network (CNN) consists of two convolution layers, two max pooling layers, a flatten layer and two fully connected layers. We use convolution neural network to extract the features in range-speed maps. The first convolution layer is a CoordConv layer, which was proposed by the authors in [14]. They added two channels which contained coordinate information to the input in order to improve the sensibility to the feature’s position of the CNN. Recurrent neural network (RNN) is actually a long short-term memory (LSTM) network. We use the LSTM network to extract the sequence data of gestures because of the excellent results of LSTM applied to sequence processing tasks [15].
We use two CRNN structures as the gesture detector and classifier respectively, and they are described in table 1. The CRNN for detector is used for judging whether the hand action exists. When the hand action is detected, the CRNN for classifier will be adopted to more range-speed maps which contain detected maps in order to extract detail features and recognize hand gesture.

| Layer     | Input       | Output       | Kernel | Input       | Output       | Kernel |
|-----------|-------------|--------------|--------|-------------|--------------|--------|
| CoordConv | 1x32x32     | 4x30x30      | 3x3    | 1x32x32     | 32x30x30     | 3x3    |
| MaxPool   | 4x30x30     | 4x15x15      | 2x2    | 32x30x30    | 32x15x15     | 2x2    |
| Conv      | 4x15x15     | 8x13x13      | 3x3    | 32x15x15    | 64x13x13     | 3x3    |
| MaxPool   | 8x13x13     | 8x6x6        | 2x2    | 64x13x13    | 64x6x6       | 2x2    |
| Flatten   | 8x6x6       | 288          | -      | 64x6x6      | 2304         | -      |
| FC        | 288         | 128          | -      | 2304        | 768          | -      |
| FC        | 128         | 54           | -      | 768         | 256          | -      |

5. Experiments and results
The nursing bed includes 6 switches, so we designed 6 gestures to control the motors. All gestures are shown in Figure 12. In order to train and evaluate the proposed FMCW radar gesture controlling nursing bed system, we gathered a data set. We invited 8 individuals to collect gestures as a training set. They performed gestures by their habits. We fed the obtained data set into the neural network for training to obtain the model.

Then, in order to verify the accuracy of the model, we invited 4 individuals to test. Instead of pressing a switch, they only need to lie on the nursing bed and make hand gestures. Gesture recognition results are sent to the Arduino through serial and a certain function is completed. The test scenario is shown in Figure 13. To test the penetration, we covered the radar with cardboard.

We tested all functions using hand gestures. We recorded the response time and control success rate during the test. The response time meant the time from the completion of the hand gesture to the rotation of the motor is calculated by taking the average of multiple people and times. The detailed result is listed in table 2. Our proposed method has a control success rate as high as 93.75% and the average response time is 1.03s.
Table 2. Response time and control success rate.

| Back-up | Back-down | Turning left | Turning right | Raising leg | Dropping leg |
|---------|-----------|--------------|---------------|-------------|--------------|
| 1.03    | 0.91      | 2.31         | 0.69          | 0.60        | 0.64         |
| 93.75   | 84.61     | 81.32        | 93.75         | 86.67       | 83.33        |

6. Conclusions
In this article, we developed an effective and practical nursing bed based on hand gesture control using a 60 GHz FMCW radar. The overall system includes a mechanical design part, a control system part and a real-time hand gesture recognition system. We adopt a rod mechanism to realize functions including frictionless back-up, integral turning over and leg raising. We use an Arduino UNO development board as the core processor, which sends instructions to the motor driver. In order to recognize gestures, we develop the Convolutional Recurrent Neural Network (CRNN) to extracted to detect and classify gestures. As a result, the system has a control success rate as high as 93.75% and an average response time as 1.03s.

In future work, we would like to improve mechanical structure stability. Also, we will add more functions on the nursing bed, such as non-contact vital signs signal monitoring using FMCW radar.

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