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RF-IDH: An intelligent fall detection system for hemodialysis patients via COTS RFID[☆]

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ABSTRACT

Unhealthy habits lead to a growing population of hemodialysis patients. The single treatment of hemodialysis is about four hours long. Therefore, patients usually go to the toilet during treatment and need to be checked for safety. However, existing fall detection techniques are often limited by factors such as privacy, signal interference, and the like. In this paper, we propose RF-IDH tackle the above issues, a dedicated system for detecting falls caused by complications in hemodialysis patients using RF signal. In RF-IDH, after collecting the signal, we process the collected data by three functional module clusters, namely signal preprocessing, residual feature extraction, hemodialysis patient's fall detection, all of which are well-designed to achieve high performance in patient's fall detection. In particular, we design a residual feature extraction (RFE) algorithm based on the hemodialysis patient safety process model, and the fall detection of hemodialysis patients is treated as a machine learning problem where four classification models are built via learning residual feature space. We implement our system on commercial off-the-shelf RFID devices and compared the evaluation metrics of four different methods in terms of system performance, efficiency, robustness, and latency. The evaluation results show that our proposed RF-IDH that optimizes the 2NN–RFE method achieves superior performance compared to other methods.

1. Introduction

1.1. Motivation

With the development of society, excessive work pressure, bad eating habits, a severely polluted environment, and many other bad habits make more and more people accept various tests for their health. Once high blood pressure, high blood fat, diabetes, obesity, and other diseases are found, it is also easy to cause kidney damage. Like this, there are many reasons for chronic kidney diseases (CKD), such as urinating, drinking too little, eating too salty, and drug abuse, etc. At present, various chronic kidney diseases will eventually progress to end-stage renal disease (ESRD). Patients may develop severe uremia symptoms and rely on renal replacement therapy to maintain normal life needs. For patients with end-stage renal disease, the globally accepted treatment is renal replacement therapy, including hemodialysis (HD) and renal transplantation (RTx). However, kidney transplants are very expensive and difficult to find a suitable kidney source. Therefore, hemodialysis as an alternative treatment is an effective means for most people to treat kidney diseases and certain immune metabolism and nervous system diseases. According to the survey data of 2016, 2.96 million people worldwide received dialysis treatment, an increase of 5.7% compared with 2015. Forty-two percent of hemodialysis patients worldwide come from the Asia-Pacific region, nearly 500 thousand Chinese people among them, 25 percent from Europe/Middle East and 23 percent from North America. It is believed that the number of new hemodialysis patients in emerging markets such as the Asia Pacific will maintain the growth rate of 6%–7%.

Hemodialysis can indeed relieve symptoms and prolong the survival time of patients. However, the treatment process of hemodialysis is not smooth. The treatment frequency of hemodialysis increases with the time of illness, usually three times a week. The time of single blood purification treatment is long, except for the first two adaptation periods, all reach four to five hours. In addition, there are many precautions and possible complications during the treatment of hemodialysis patients. It is gratifying to note that hemodialysis patients are usually able to take care of themselves, but this also entails many potential

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safety risks. Intradialytic hypotension (IDH) and muscle spasm are the two most common complications of hemodialysis. The main reason is that hemodialysis is a blood purification technology based on the principle of membrane balance. It allows blood to pass through membranes with many small holes (or channels, medically known as semipermeable membranes), which allow small molecules to pass through, while large molecules cannot. In addition, the contact between semipermeable membranes and dialysates containing certain chemicals can achieve the purpose of removing harmful substances from the body and replenishing substances needed by the body. However, this hemodialysis mechanism often leads to excessive dehydration or excessive dehydration speed, which leads to the decline of blood volume or muscle spasm. When the patient's body position changes, hemodialysis hypotension or muscle spasm is prone to occur and a typical scene of the real treatment period is that hemodialysis patients are more likely to go to the toilet because a single blood purification treatment lasts for up to four or five hours. After the patients go to the toilet, they suddenly change from a sitting position to standing position. There is a certain probability of hemodialysis hypotension or muscle spasm caused by body position changes, which may lead to the risk of falling. Once the patient falls down, the medical staff must respond in time, otherwise, the patient will be in danger of serious insufficiency of vital organ blood supply. Therefore, taking into account all the factors of the above analysis, the hospital blood purification center does need to deploy a high-performance intelligent fall detection system that meets the privacy requirements of hemodialysis patients in the toilet.

1.2. Proposed approach

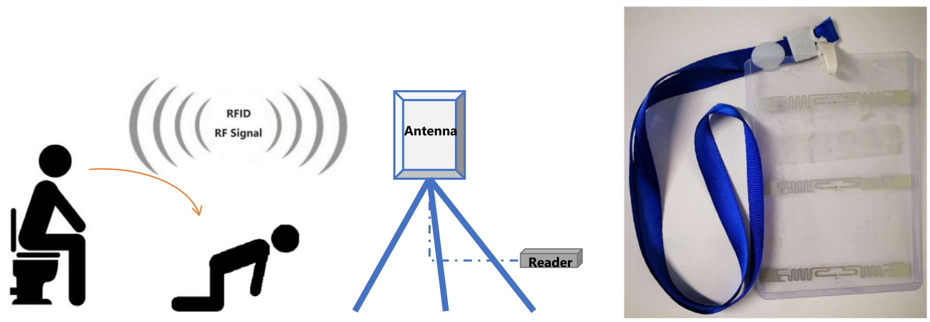
In this paper, we propose an RF-IDH system, an intelligent fall detection system for hemodialysis patients with a complication of hypotension or muscle spasm based on RF signal, to meet the actual needs of hospital blood purification centers. RF-IDH uses a commercial off-the-shelf (COTS) RFID reader with one antenna and three EPCglobal C1G2 standard passive tags attached to a badge with adjustable lanyard length. Each tag is deployed horizontally in parallel to achieve multi-speed sample acquisition. In addition, multi-tag deployment also plays the role of redundant backup in the real test environment, preventing the hemodialysis patient from absorbing the backscattered signal of some labels after the body falls. The RFID reader antenna, which is placed in front of the toilet seat, continuously interrogate the tag array and obtain the backscattered RF signals from each tag. For each antenna–tag pair, the reader obtains a sequence of RF phase values and a sequence of received signal strength indicator(RSSI). Fig. 1 shows an overview of our system.

The basic idea of our RF-IDH system is to collect phase and RSSI information of RF signals and perform a series of signal preprocessing operations on these collected data. Then, through careful analysis of the rules of collecting data sample sets in the safe toilet process of hemodialysis patients, a reasonable and effective objective function for the optimization problem is established to derive the process model of hemodialysis patients safely complete the process of going to the toilet. Then, we design a residual feature extraction (RFE) algorithm based on the hemodialysis patient safety process model, and the fall detection of hemodialysis patients is treated as a machine learning problem where a series of classification models are built via learning residual feature space constructed by our proposed RFE algorithm. We implement our system on commercial off-the-shelf RFID devices and compared the evaluation metrics of the four methods of 2NN–RFE, LR–RFE, RF–RFE and SVM–RFE in terms of system performance, system efficiency, system robustness, and system latency.

1.3. Technical challenges and solutions

There are many technical challenges that we will address in this paper. The first technical challenge is how to deal with the variety of fall downs that can occur when a hemodialysis patient gets up and walk after completing the defecation process. Therefore, in order to find a practical solution to the diversity of hemodialysis patients' fall actions, we have made many technical attempts in the early stage, including solutions based on statistical feature extraction in sliding windows [1–3] and solutions based on Kalman filter tracking [4–6]. After careful comparison and analysis of the experimental data, we first denied the solution through the statistical feature extraction based on the sliding window, because the experimental data we collected needs to take into account the real needs of hospital blood purification centers, which did not deliberately limit the patient's fall action, but try to ensure that the collected data sample set covers different fall directions and areas, different fall times, fall speeds, and different down postures. Therefore, a sample dataset with random diversity is destined to be too difficult to find common features through the sliding window without manual intervention of the fall action. The solution based on statistical feature extraction in the sliding window is impractical, so what about the solution based on Kalman filter tracking? Researchers familiar with Kalman filter are aware of the two major difficulties in establishing Kalman filter tracking. The first difficulty is how to establish a suitable process model to describe the state transfer of the state vector designed by Kalman filter with a specific state transfer function. The second difficulty is how to establish the corresponding relationship between the state space and the measurement space, and convert the prior value predicted by the process model into the phase or RSSI of the RF signal used in the measurement space with a specific measurement function. Given the diversity of falls in hemodialysis patients, the Kalman filter tracking solution does not seem to be easier or more feasible than the first one based on sliding window statistical characteristics extraction. However, we can completely abandon the specific constraints in Kalman filter design process, not to consider the two specific difficulties mentioned earlier, but to stand on a higher and more abstract level, to learn from the principles of Kalman filter and the ideas behind it. In fact, many members of the Bayesian filtering family, including Kalman filter, use different mathematical methods, but fundamentally, they only do one thing, that is, to make a proper choice between prior prediction and actual measurement. As for the selection of a prior prediction model, it depends on the design objective of the filter. Therefore, we rethink the problem that the RF-IDH system really needs to be solved for the hospital. Nobody cares about the types of falls of hemodialysis patients. In fact, the blood purification center only cares about whether the diversity falls of hemodialysis patients can be detected with high accuracy, high efficiency, high robustness and low delay by our intelligent system. If we think backward, it is easy to find such a rule. Compared with the ever-changing fall movements, the process of hemodialysis patient safety process is relatively simple, just normal standing and walking after completing the defecation process. Then, we established a reasonable and effective objective function for optimization problem and derived hemodialysis patient safety process model from measurement space based on dynamic time warping (DTW) [7].

With the help of the hemodialysis patient safety model, we need to address the second technical challenge of how to extract appropriate features to meet the performance requirements of various aspects of the system. Similarly, here we draw on the idea of adaptive filtering and fusion sensing. By calculating the residual between the feature of the RF signal in the measurement



(a) Antenna deployment. (b) Tag deployment.

Fig. 1. System Overview. (a) Antenna deployment. (b) Tag deployment.

space and the hemodialysis patient safety process model, we propose a residual feature extraction (RFE) algorithm based on DTW. The phase and RSSI information of the RF signal is used as the input of the RFE algorithm to obtain the fusion sensing feature space. The detection accuracy and robustness of the system are guaranteed compared with the traditional way of using the phase or RSSI information of the RF signal alone. The algorithm eventually returns the feature matrix composed of the vector of residual phase feature and residual RSSI feature.

We make four key contributions in this paper. As far as I know, we have taken the lead in proposing an intelligent fall detection system for hemodialysis patients with a complication of hypotension or muscle spasm based on RF signal for hospital blood purification centers. Second, we propose an effective and feasible RFE algorithm for deriving hemodialysis patient safety process model from measurement space based on DTW and constructing the residual feature space of the system by calculating the residual between the phase/RSSI of the RF signal in the measurement space and the derived process model. Third, our proposed 2NN–RFE method takes advantage of the fusion of residual information of phase and RSSI of the RF signal and achieves superior performance over traditional methods using phase or RSSI of RF signal alone. Last, we implemented RF-IDH using COTS RFID reader with one antenna and three EPCglobal C1G2 standard passive tags attached to a badge with adjustable lanyard length for multi-speed sample acquisition and redundant backup in the real test environment, preventing the hemodialysis patient from absorbing the backscattered signal of some labels after the volunteer falls. The results show that RF-IDH achieves a F1 score of more than 0.99 in both the cross-validation stage and the final test data evaluation stage. And as the training sample ratio increases, the evaluation metric approaches the maximum metric it can achieve. Moreover, the experiment results also show that RF-IDH is robust against the influence of individual diversity by different volunteers and has an acceptable fall recognition latency.

2. Related work

Camera-based fall detection: F. Merrouche, B. Ni et al. [8,9] proposed new methods for fall detection using depth camera by exploiting the advantages of Kinect. S. Zambanini et al. [10] proposed an approach for the detection of falls based on multiple cameras. T. Zhang et al. [11] proposed a falling detection algorithm based on a humanoid robot to monitor and detect the motion of the elderly who live alone. The Pi Camera system uses low-cost Pi Camera mounted on Raspberry Pi to monitor and detect a person's fall-like movements [12]. P. S. Ong et al. [13] proposed a solution of FPGA-based visual based fall detection to meet the stringent real-time requirement. However, Camera-based detection schemes are often limited by light and shooting perspective. Especially in this research, camera-based detection schemes are rejected because of a violation of the privacy of hemodialysis patients.

Fall detection based on RF signal: Sensing-Fi system is comprised of harnessing Wi-Fi Channel State Information (CSI) coupled with ground-mounted accelerometer to detect floor vibration [14]. A. Alesin et al. [15] proposed a low budget multi-functional wearable device which can be worn as a bracelet or alternatively on one's upper leg, ankle or upper arm. Wickramasinghe, A. et al. [16] proposed a bed-egress movement detection framework which integrated a wearable batteryless RFID sensor with the accelerometer. Wang, P. et al. [17] proposed a safety monitoring platform for nursing care service with a wearable vest incorporating accelerometer-based fall detection and message notification service for the elderly with dementia to assist managers to improve the care quality in Hospital. Wickramasinghe, A. et al. studied the feasibility of passive computational RFID sensors for ambulatory monitoring and recognizing transfers out of beds or chairs and walking in [18]. J. He et al. proposed a 3-axis accelerator with a motherboard and Bluetooth and a gyroscope built-in information on the automatic fall detection and alarm system consisting of custom vests and mobile smartphones [19]. D. Chen et al. also proposed an effective fall detection algorithm using tri-axis accelerometers [20]. B. Najafi et al. [21] proposed a new physical activity monitoring method that can detect the body posture of an elderly person using only one motion sensor connected to the chest. Zhu, L. C. et al. proposed TagCare to detect motion detection and fall behavior recognition in the elderly [22]. W. Cao et al. proposed a fall detection system that uses off-the-shelf Wi-Fi devices to collect fluctuating wireless signals as an indicator of human behavior [23]. Yao, L.et al. proposed a device-free, real-time posture recognition technique using an array of pure passive RFID tags [24]. Fakhrulddin, A. H. et al. proposed research explored how to apply CNN to streaming sensor data, collected from Body Sensor Networks (BSN), in order to improve the fall detection accuracy [25]. The RTagCare system leveraged RFID localization technology, 3D-accelerometer base human activity identification and data mining algorithm to overcome traditional activity recognition system issues [26]. Torres, R. L. S. et al. investigate a device free method to detect falls by using simple batteryless radio frequency identification (RFID) tags in a smart RFID enabled carpet [27]. Most of the above fall detection solutions usually require the integration of special sensors such as multi-axis accelerometers, gravimeters, etc. These programs are not limited to hemodialysis patients who need to cooperate but often set specific action sequence requirements. Otherwise, fall detection schemes based on multi-axis accelerometers or gravimeters are difficult to apply in real-world scenarios. In addition, a small part of the above solutions is based on wireless signals, such as Wi-Fi, RFID, etc., but their performance and robustness usually do not meet the needs of hospital blood purification centers.

3. RF-IDH

3.1. System overview

In this section, we analyze how to properly preprocess the RF signal, and how the proposed RFE algorithm extracts the residual feature vector required by the machine learning model from the preprocessed data. We call this method RF-IDH because it is a dedicated intelligent system for the hospital blood purification center to detect the safety process of hemodialysis patients in the toilet.

Our basic idea is to collect the phase and RSSI information in the backscattered signal of the RFID passive tags through the RFID reader antenna. The preprocessed data is then carefully analyzed to extract appropriate features for the machine learning method to train the evaluator to alert the medical staff that the hemodialysis patient has a random fall in the toilet. The most naive idea is to directly use the phase and RSSI time series of the preprocessed radio frequency signal as the feature space, but this will cause the machine learning process to fail due to the dimensional disaster or dimension explosion, even if it is lucky that the mode can be run, but the costs of the calculation time and the required hardware resources are also unimaginable, so this method has no practical significance. In order to increase the feasibility of the system, it is natural to first find ways to reduce the dimension of the feature space, and think of using the statistical characteristics of the pre-processed radio frequency signal related time series as the feature space, the simplest and crudest method is to use the minimum, maximum, mean, median, standard deviation, etc. However, the above-mentioned common statistical features cannot truly represent a time series data, because the time series data with similar general statistical features may have completely different shapes. Using the general statistical feature method, compared with the whole time series as the feature space method, the feasibility is guaranteed, but the system accuracy and false positive rate are really worrying. In order to increase the performance of the system, we try to find features that can more accurately represent the complete time series from the backscattered signals. We have tried many statistical feature analysis and experimental verification based on different sliding windows. But our initial attempts failed because of the randomness and diversity of the hemodialysis patients' fall actions in the real environment. Finally, we use the reverse thinking method to derive the hemodialysis patient safety process model and extract the phase residual feature and RSSI residual feature of the RF signal to construct the feature space according to the derived process model. Finally, a variety of machine learning methods are used to learn the feature space and target space, and the corresponding performance evaluation is carried out. In addition, to speed up the response to the actual test environment, the RF-IDH system performs local persistence operations.

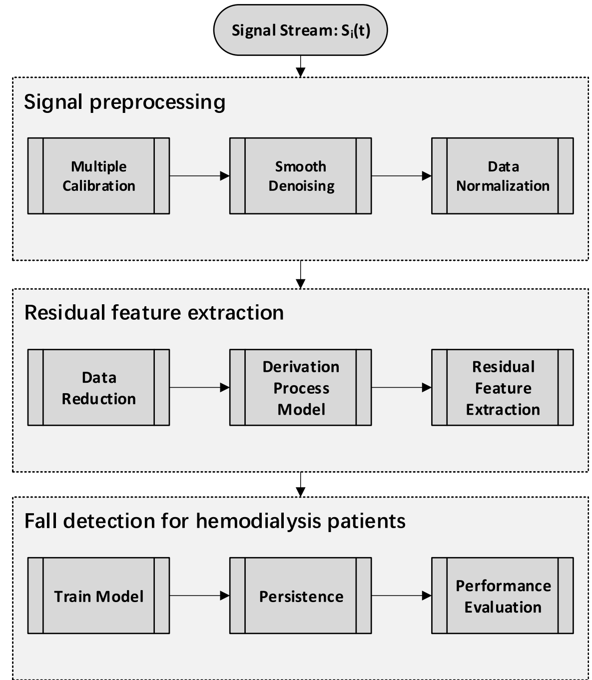


Fig. 2. System architecture.

3.2. System architecture

Our goal is to accurately, efficiently and robustly estimate the fall of hemodialysis patients by the trend of backscatter signals collected from the toilet environment of hospital blood purification center. We describe the processing flow of the collected backscatter signal of the RFID tags in the whole RF-IDH architecture and present its technical details in the following parts. As shown in Fig. 2, our approach consists of three module clusters, namely signal preprocessing, residual feature extraction, and fall detection for hemodialysis patients, all of which are well-designed to achieve high performance in patient's fall detection.

RF-IDH System takes as input the time-series signal $S_i(t)$ received from each tag of the tag array, including both the phase and RSSI information. The signal preprocessing module first calibrates the measurement signal by unwrapping phase and eliminating diversity in measured values of the tag array. Next, we perform appropriate filtering on the calibrated signal to achieve a smooth denoised signal. Finally, we normalize the filtered signal to prevent the absolute variation of the time series amplitude from affecting the modeling and feature extraction of subsequent modules. Then, the residual feature extraction module uses the preprocessed data as the input of our proposed data reduction method to derive the safety process model of the hemodialysis patient. After deriving the hemodialysis patient safety process model, the residual extraction module extracts the residual feature matrix of the backscattered signal caused by the motion of the hemodialysis patient, based on the hemodialysis patient safety process model. Finally, the hemodialysis patient falls detection function module trained the constructed residual feature space by four methods of 2NN–RFE, LR–RFE, RF–RFE, and SVM–RFE. Then the fitting model is tuned and persisted for optimized performance. The evaluation results show that all classifiers based on our proposed RFE algorithm have achieved good results and our proposed RF-IDH that optimizes the 2NN–RFE method achieves superior performance in four different dimensions of performance, efficiency, robustness, and latency compared to other methods. The results show that RF-IDH achieves a F1 score of more than 0.99 in both the cross-validation stage and the final test data evaluation stage. And as the training sample ratio increases, the evaluation metric approaches the maximum metric it can achieve. Moreover, the experiment results also show that RF-IDH is robust against the influence of individual diversity by different volunteers and has an acceptable fall recognition latency.

3.3. Signal preprocessing

We use a commercial RFID reader connected with one antenna to get the tag array's backscatter signal, as illustrated in Fig. 1. The RF-IDH system resolves the RSSI and phase data of the RF signal provided by the commercial RFID reader, wherein the RSSI characterizes the power of the received signal, and the phase data is a common attribute of the wireless signal as the signal amplitude and frequency.

When the raw signal has been collected, if we expect to resolve the RF phase from it, the primary task is to calibrate the measurement signal by stitching phase of the tag array, because the phase value parsed by the commercial reader is a periodic function with a phase value range of 0 to 2π. If it is desired to clearly characterize the offset of the received signal from the transmitted signal by the RF phase, then corresponding de-cycle processing must be performed. Let $d(t)$ be the distance between the reader antenna and one tag at time t, the signal traverses a round-trip distance of $2d(t)$ in each backscatter communication. The phase rotation at time t output by the reader [28] can be expressed as:

$$\begin{cases} \Theta(t) = [2d(t) \times \frac{2\pi}{\lambda} + \Theta_{diff}] \bmod 2\pi & \text{(a)} \\ \Theta_{diff} = \Theta_{TC} + \Theta_{RC} + \Theta_{Tag} & \text{(b)} \end{cases} \tag{1}$$

where λ is the RF signal's wavelength, variable refers to phase rotation diversity term, which is caused by the hardware characteristics, including the phase offset introduced by the antenna's transmission circuit, the antenna's receiver circuits and the tag's reflection characteristic respectively. After we stitch the phase values and remove the periodicity among the phase values, we need to perform the necessary calibration on RF-IDH. Since we use the same antenna, we do not have to consider the diversity differences caused by the antenna transmit and receive circuits, we only consider eliminating the diversity differences between the tags in the tag array used by RF-IDH.

After the original signal stream is calibrated, the next thing to do is signal smoothing and noise reduction. Further, we utilize the Savitzky-Golay Filters, which are optimal in the sense that they minimize the least-squares error in a convolution process for noisy data, to filter the corresponding noise contained in the calibrated data and smooth the calibration data. The smooth denoising operation performed by Savitzky-Golay filters tends to increase the signal-to-noise ratio (SNR) without greatly distorting the signal and preserving some distribution characteristics such as relative shape and trend, which actually make they are more effective than other standard averaging FIR filters in our circumstances. Finally, we normalize the filtered signal to prevent the absolute variation of the time series amplitude from affecting the modeling and feature extraction of subsequent modules.

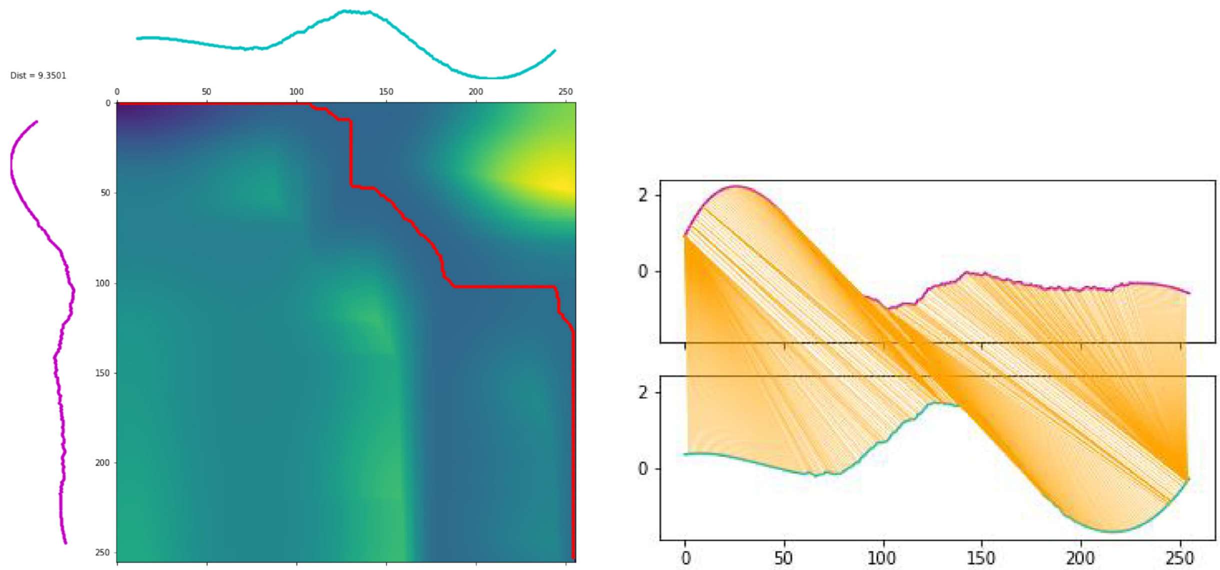
3.4. Residual feature extraction

After completing the work of the signal preprocessing module, we are working to solve the technical challenge that how to find a practical solution to deal with the diversity of fall downs that can occur when a hemodialysis patient gets up and walks in the toilet of the hospital blood purification center. Given that the real need for hospital blood purification centers is to accurately detect the random diversity of fallouts that may occur in hemodialysis patients, we do not limit the sequence combination of fallbacks during the experiment. We try to ensure that the collected sample data sets cover different fall directions and areas, different fall times, fall speeds, and different down postures. Therefore, the random diversity of hemodialysis patients' fall actions makes the two initial solutions, which are based on sliding window statistical features and Kalman filter-based tracking, facing the lack of feasibility. However, the initial attempt naturally made us think backward about the solution to the problem. In fact, nobody cares about the types of falls of hemodialysis patients. The blood purification center really cares about the performance of the system that patients can accurately judge no matter what kind of action they fall. If we think backward, it is easy to find such a rule. Compared with the ever-changing fall movements, the process of hemodialysis patient safety process is relatively simple, just normal standing and walking after completing the defecation process. With the help of the derived hemodialysis patient safety model, our proposed RFE algorithm transforms the research problem into the optimization problem of the objective function and uses the idea of DTW to measure the difference between the time series. We establish the objective function corresponding to the research question as follows:

$$\arg\min_{\bar{x}\epsilon\mathbb{E}} \sum_{i=1}^{N} Dist^2\,(\bar{x}, z_i) \tag{2}$$

This definition gives a set of measurements $z\epsilon\{z_1, z_2, \ldots, z_N\}$ in space $\mathbb{E}$, and $\bar{x}$ represents a priori prediction of the hemodialysis patient safety process model which minimizes the sum of the squares distance to the set. In our case, the difference between the prior predicted value and the measured value is determined by the DTW distance, rather than the traditional Euclidean distance (ED). Euclidean distance is simply the sum of the squared distances from each n_{th} point in one time series to the n_{th} point in the other and obviously hard to meet the requirement to calculate the distance between different long time series. Instead, dynamic time warping algorithm is able to find the optimal alignment between time series to overcome this limitation and give intuitive distance measurements between time series if time series may be warped non-linearly by stretching or shrinking it along its time axis. Taking two randomly selected samples as an example, due to the diversity of volunteer actions, for example, some volunteers stand faster and some stand slower. The time series of RSSI features of the two safety process samples are not consistent. Comparing the calculation results of the Euclidean distance and the dynamic time regularization distance, the distance measurement values of the time series are 21.3792 and 9.3501, respectively. The above results prove that the distance between time series calculated by the dynamic regularization algorithm is more intuitive. In this case, the processing flow of dynamic time warping is shown in Fig. 3. The mechanism behind the dynamic time warping algorithm is to first fill the cost matrix with a dynamic iterative method and then inversely greedy search and calculate the optimal warping path, finally, compute the distance of the optimal warping path.

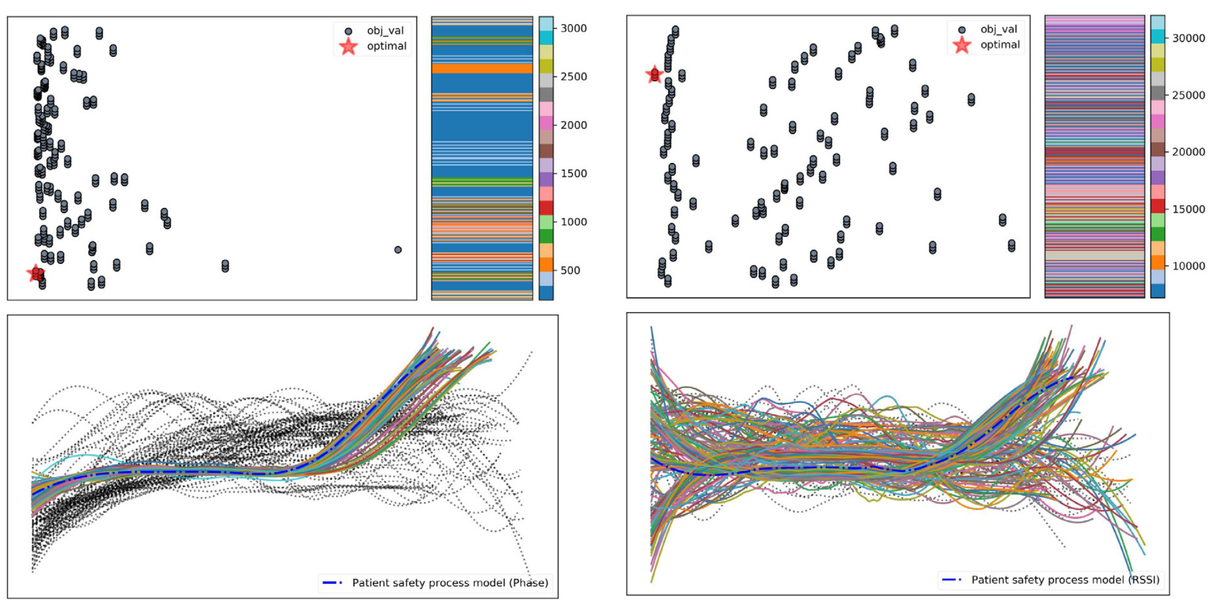
After we convert the research problem into the solution to the optimization problem of the objective function and clarify the objective function using the DTW method to measure the distance, the RFE algorithm for establishing the hemodialysis patient fall detection feature space can be summarized as Algorithm 1 by pseudo code. Algorithm 1 firstly extracts the subsample data set of the hemodialysis patient safety process and then calculates the 97.5% confidence interval of the subset by statistical methods, which will eliminate those bad samples with abnormally short lengths due to backscatter signal absorption and interference of part tags caused by falling action. After that, we compare the distance between the a priori prediction and all measurements by the dynamic time warping method and calculate the sum of the squares of these distances to obtain the optimal solution of the objective function. The visualization process and results of the hemodialysis patient safety process model derived from RF phase and RSSI are shown in Fig. 4. Specifically, Fig. 4(a) and (b) are composed of three subgraphs. The gray markers in the upper left subgraph are the calculated values of the objective function of formula (2), and the red marker is the optimal solution of the objective function. The color spectrum of the upper right subplot represents the distribution of the objective function values. The black dotted line in the lower sub-picture indicates the fall example, the colored solid line indicates the safety example, and



(a) The red optimal warping path with visual cost matrix and origin time series.

(b) The resulting optimal alignment between time series.

Fig. 3. The process of aligning time series by dynamic time warping. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)



(a) Patient safety process model (Phase).

(b) Patient safety process model (RSSI).

Fig. 4. The visualization process and results of the hemodialysis patient safety process model.

the blue dot-dashed line indicate the results of the hemodialysis patient safety process model.

Finally, we calculate the residuals of the prior prediction optimal solution and the measured values to form the residual feature space as the output of Algorithm 1.

4. Implementation and evaluation

After we complete the extraction of residual features and construct the residual feature space, we use a variety of machine learning methods to train the residual feature space, and persist the trained classification estimator, and then evaluate the performance of the system.

4.1. Implementation

4.1.1. Hardware

Our RF-IDH system consists of a COTS UHF RFID reader (Impinj R420) continuously interrogating the tag array and obtain the backscattered RF signals from each tag, a directional antenna linked to the reader and deployed approximately 1.8 m in front of the toilet seat, and a set of EPCglobal C1G2 standard passive tags horizontally attached to a badge with adjustable lanyard length ensuring that the lower edge of the tag array maintains a similar height off the ground during signal collection.

Algorithm 1 Residual Feature Extraction Algorithm

Input: The set of RF phase/RSSI series to extract residual feature $\mathbb{S}$
Output: The residual feature space $\mathbb{D}$

for s in $\mathbb{S}$ **do**
    if s is safe process **then**
        $\mathbb{S}_1 \leftarrow s$
    end if
end for
$\mathbb{E} \leftarrow$ Calculate 97.5% confidence interval for $\mathbb{S}_1$
$d_{min} \leftarrow \infty$
for (x, z) in $\mathbb{E}$ **do**
    d $\leftarrow$ Compute sum of squares of DTW distance by Eq. (2)
    if d $< d_{min}$ **then**
        $d_{min} \leftarrow$ d
        $\bar{x} \leftarrow$ x
    end if
end for
for z in $\mathbb{S}$ **do**
    f $\leftarrow$ Compute DTW distance for (z, $\bar{x}$)
    $\mathbb{D} \leftarrow$ f
end for

Table 1
Falling simulation of hemodialysis patients.

No.	Description of the Fall Action
01	Standing completed + Falling to the front area.
02	Standing completed + Falling to the right front area.
03	Standing completed + Falling to the left front area.
04	Standing completed + Falling to the right area(Sitting Posture).
05	Standing completed + Falling to the left area(Sitting Posture).
06	Standing completed + Waking + Falling to the front area.
07	Standing completed + Waking + Falling to the right front area.
08	Standing completed + Waking + Falling to the left front area.
09	Standing completed + Waking + Falling to the right area(Sitting Posture).
10	Standing completed + Waking + Falling to the left area(Sitting Posture).
11	Standing halfway + Falling to the front area.
12	Standing halfway + Falling to the right front area.
13	Standing halfway + Falling to the left front area.
14	Standing halfway + Falling to the right area(Sitting Posture).
15	Standing halfway + Falling to the left area(Sitting Posture).

4.1.2. Software

The computer equipped with the RF-IDH system is connected to the Ethernet port of the RFID reader through the network cable to complete the collection and analysis of the RF signal. Our RF-IDH system extracts low-level signal information from the Impinj R420 reader by integrating Octane SDK, an extension of the LLRP Toolkit, which supports the collection and analysis of RF signal phase, RSSI and Doppler shifts. After that, we accomplished the remaining data analysis work according to the system architecture and processing flow described in the previous chapters.

4.1.3. Data collection

In order to establish the sample dataset to meet the needs of the hospital blood purification center, our experimental arrangement considers as much as possible the impact of different patients' fall factors, including the direction of fall, posture, speed, etc. The simulation action arrangement is shown in Table 1 and Fig. 5.

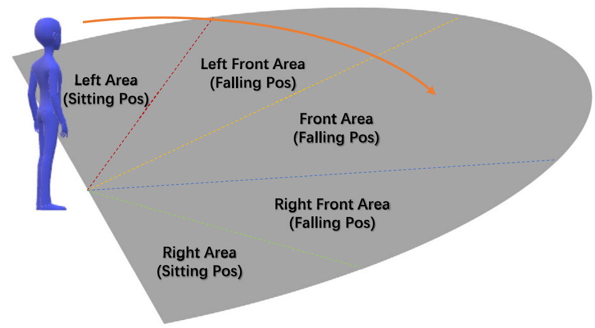


Fig. 5. Demonstration of the division of the fall area and posture in the experiment.

4.2. Evaluation

4.2.1. System performance metrics

For detecting a fall event in a hemodialysis patient, the predictable outcome of the RF-IDH system can be are divided into two categories: positive (classifying the patient as safety) or negative (classifying the patient as having a fall). However, the estimated result for hemodialysis patient may or may not match the patient's actual status. Therefore, the detection performance of the RF-IDH system is finally based on the following four types of statistical events: True Positive (TP): hemodialysis patient correctly identified as safety. False Positive (FP): hemodialysis patient incorrectly identified as safety. True Negative (TN): Hemodialysis patient correctly identified as having a fall. False Negative (FN): Hemodialysis patient incorrectly identified as having a fall. Finally, we calculate the precision and recall rate separately and then get our desired system performance metric F1, which is the harmonic mean of the equal weight precision and recall rate. The formula for the above calculation process is as follows:

$$F1\ score = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{3}$$

$$Recall = \frac{TP}{TP + FN} \tag{4}$$

$$Precision = \frac{TP}{TP + FP} \tag{5}$$

The above metrics are evaluated using an advanced stratified shuffle cross-validation strategy, which guarantees to sample discrete and equal proportions of different types of data points, to split data into train and validation sets in the training and debugging model stage. In the subsequent parameter tuning section, feature selection comparison section, and learning efficiency comparison section, in order to meet the strict requirements of the hospital for hemodialysis patients safety, we do 100 iterations of random shuffling and segmentation of the dataset, and guarantee each train and validation fold keeps 50% of the samples as the validation dataset, and the cross-validation strategy also ensures that relative class frequencies are approximately preserved in each train and validation fold. In the following subsections of system robustness analysis and system delay analysis, instead of using cross-validation strategy, we use reserved test data sets, which contain new data that we have never seen before, as production stage tests, to prevent validation overfitting. At the same time, in order to get the best performance of the model in the final test data evaluation stage, we use all the data used in the training and debugging model stage, including the training and validation set used in cross-validation before.

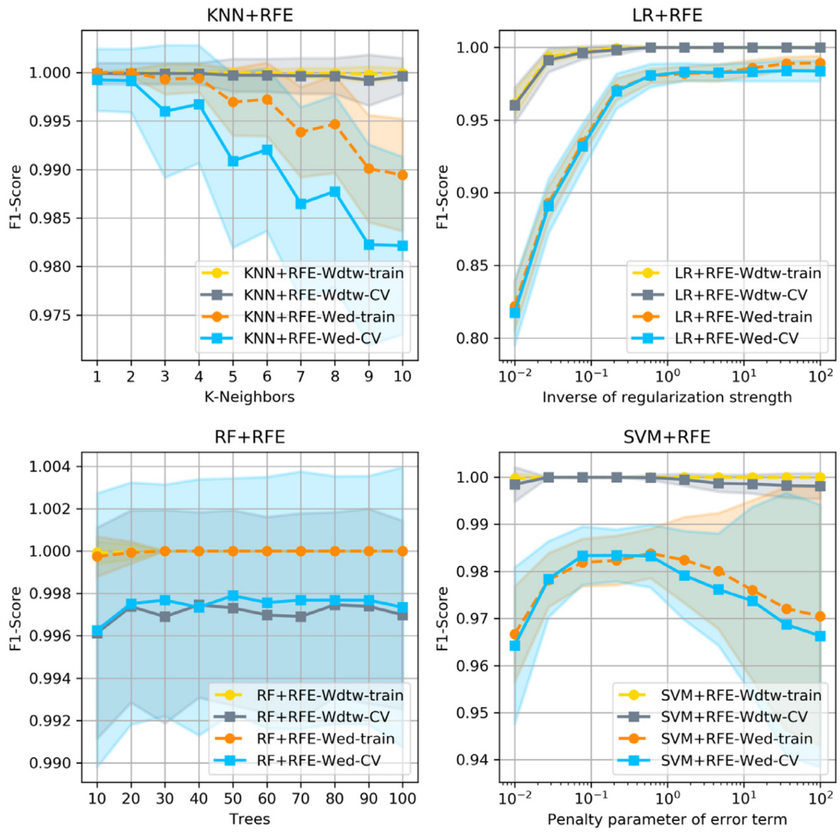


Fig. 6. Parameter tuning.

4.2.2. Parameter tuning

After we determined that the F1 score was set as a measure of RF-IDH system performance, we used four machine learning methods to fit the proposed hemodialysis patient residual feature space for the classification model. First, let us take a look at these several machine learning methods: K-nearest neighbor classification, logistic regression classification, random forest classification and support vector classification algorithm. KNN classification algorithm is a common non-parametric method which estimates classification results by a majority vote of its neighbors. Logistic regression is a maximum-entropy classification algorithm, which uses a sigmoid function to model and output the probabilities describing the possible outcomes of a single trial. Random forests are an ensemble classification algorithm that operates by constructing a multitude of decision trees at training time. SVM classification algorithm learns the optimal separating hyperplane by maximizing the distance to the nearest training data point of any class.

Then, we select the specific parameters of each classifier based on experience, and the purpose is to find the specific parameter values of the optimal performance of each classifier, including the number of the nearest neighbor nodes of KNN classification algorithm, the inverse of regularization strength of LR classification method, the number of trees in the forest in the RF classification model, and the penalty value of the error term in the SVM classification algorithm. The parameter tuning of different classifiers is shown in Fig. 6.

From the data in Fig. 6, we selected the specific parameter values of the optimal performance of each classifier: setting the number of the nearest neighbor nodes of KNN classification algorithm (using uniform weights) to 2, setting the inverse of L2 regularization strength of LR classification method (using L-BFGS-B as the optimization problem algorithm, using 10^{-4} as the tolerance of stopping criteria, using balanced class weights) to 10, setting the number of trees in the forest in the RF classification model (using 10^{-7} as the early stopping threshold for tree growth and using balanced class weights) to 40, and setting the L2 penalty value of the error term in the SVM classification algorithm (using 10^{-4} as the tolerance of stopping criteria and using balanced class weights) to 0.1.

4.2.3. Comparison of feature selection

After selecting the optimal parameters of different classifiers used in the experiment, we then compare the effects of different feature selection on system performance. Specifically, we compare the system performance of our proposed residual feature extraction algorithm in the case of selecting different residual features, including using only phase residual features with DTW/ED method, using union phase and RSSI residual features with DTW/ED method, using only RSSI residual features with DTW/ED method. The performance of the residual feature extraction algorithm with different features is shown in Fig. 7.

From Fig. 7, we can draw the following three conclusions. First, regardless of the features selected, our proposed patient safety process model and RFE algorithm always achieve good system performance, because even the worst feature selection F1 score exceeded 0.92. Second, by comparing the cluster features performance of Euclidean distance and DTW distance, it is obvious that when Euclidean distance is used as the residual calculation method of our RFE algorithm, the cluster performance, regardless of the four different classification methods, is weaker than the case of using dynamic time wrapping. Third, when using the same residual calculation method and classifier, the dual residual feature space of our RFE algorithm using the phase and RSSI of the RF signal is always better than using independent features.

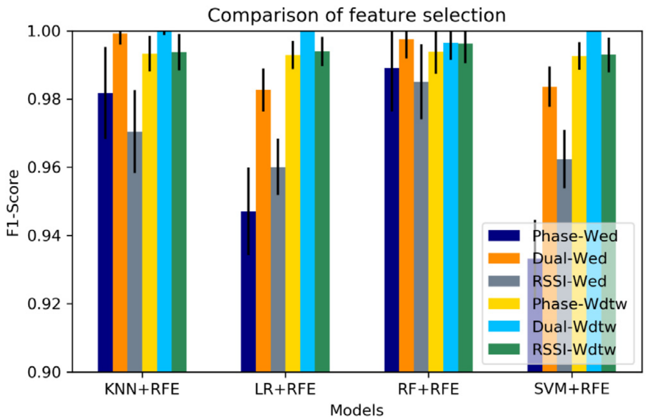


Fig. 7. Comparison of feature selection.

In summary, our proposed RFE algorithm will obtain the best performance when using the DTW distance to calculate the dual residual feature matrix as the feature space of the system.

4.2.4. Comparison of learning efficiency

According to the parameter tuning process of different classifiers shown in Fig. 6, we select the optimal specific parameters for each classifier and use this parameter to analyze the learning efficiency of different classifiers. Fig. 8 clearly shows the diff-performance of different classifiers in the case of different training sample data ratio.

First we can see that our proposed patient safety process model and RFE algorithm can provide effective assistance for different classifiers in efficiency, especially at very low training sample ratios, and with the increase of training sample data, the performance of some classifiers is almost optimal. Next, we can find another disadvantage of using Euclidean distance as the residual calculation method is that they lag behind the DTW method in the learning efficiency dimension and can only achieve performance indicators of 0.90 to 0.97 at low training sample ratios. In addition, it is worth mentioning that the RF classification algorithm is the least feasible, not only because its performance eventually lags behind other algorithms, but also the training cost of the RF method is far superior to other classification methods.

4.2.5. Sensitivity to different volunteers

Since the system robustness analysis belongs to production test stage, we no longer use the cross-validation strategy used in the training and debugging model stage. Here we use reserved test data sets that contain new data that we have never seen in training and debugging model stage. In addition, in order to obtain the best robustness performance of the system, we train four different models using all the data available of the training and debugging model stage as the training sample set of the final test data evaluation stage. Fig. 9 shows the F1-score by different volunteers of different classifiers, all higher than 0.88, indicating that the RFE algorithm used in the system is freed from the influence of individual diversity. It is particularly important to note that if the optimized 2NN is selected as the classifier for this study, the F1 measurements will all exceed 0.96, regardless of who the participants are.

4.2.6. System latency analysis

Undoubtedly, it is crucial to quickly detect a hemodialysis patient's fall, because the sooner the medical specialist is alerted to rescue, the better the patient's rescue effect will be. The alarm delay of the RF-IDH system is mainly composed of two parts,

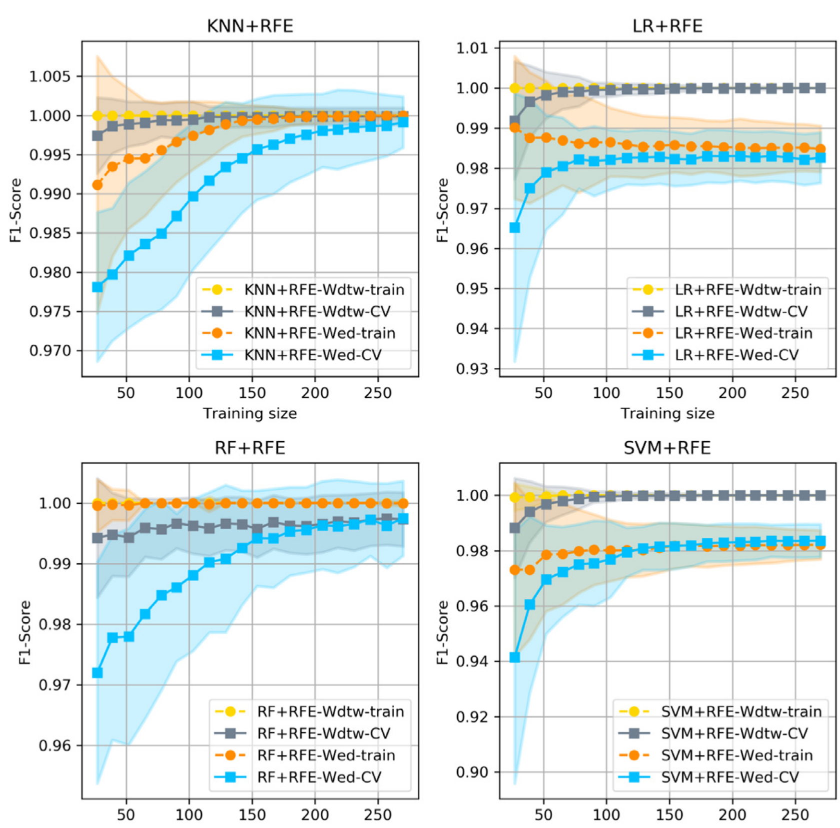


Fig. 8. Comparison of learning efficiency.

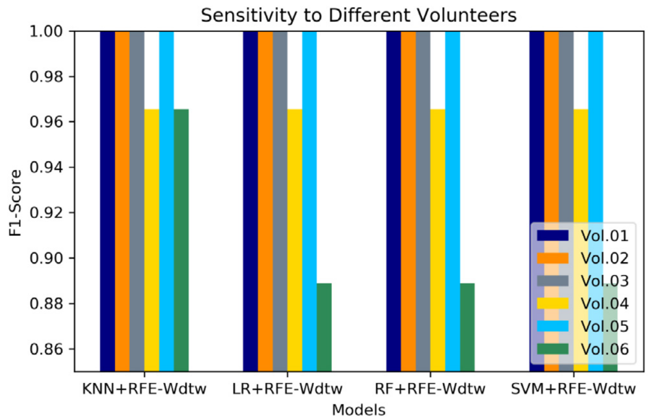


Fig. 9. Sensitivity to different volunteers.

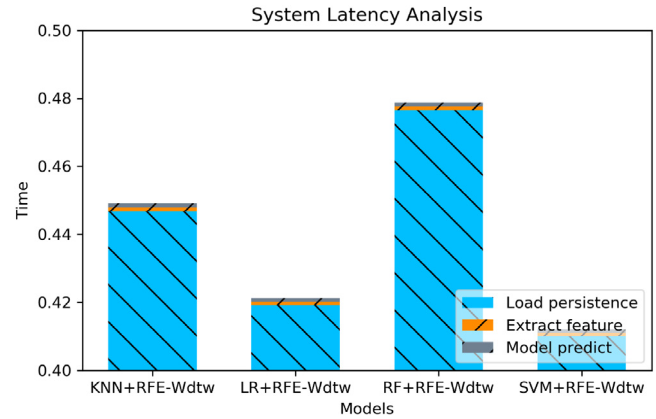


Fig. 10. System latency analysis.

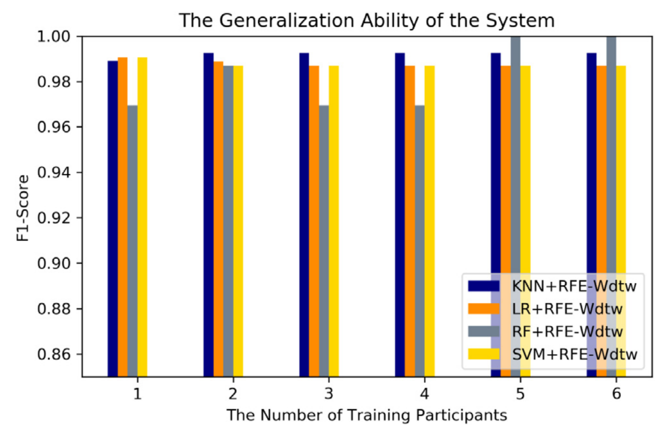


Fig. 11. System generalization ability analysis.

which are the fixed RF signal acquisition delay and the estimated delay of whether the hemodialysis patient is safe. Since system latency analysis belongs to final test data evaluation stage, we use reserved test data sets that contain new data that we have never seen before, rather than cross-validation strategies. At the same time, in order to get the best performance in the final test data evaluation stage, we train four different models using all the data available in the cross-validation strategy of the training and debugging model phase as the training sample set of the final test data evaluation stage. In addition, in order to reduce system latency, we persistent the trained final for the final test data evaluation stage. So the ultimately estimated delay consists of three parts, namely the persistent loading delay, the residual feature extraction delay, and the model prediction delay, as shown in Fig. 10.

Fig. 10 shows that the four different classification algorithms combined with our proposed RFE algorithm can control the system estimated delay within 0.50 s, and our optimized 2NN–RFE model is even controlled within 0.45 s.

4.2.7. System generalization ability analysis

If RF-IDH is expected to become an effective and reliable intelligent IoT medical system, the generalization ability of the system is crucial. Limited by objective conditions, at this stage we cannot verify the generalization ability of the system by detecting the fall of a large number of hemodialysis patients, but we can analyze the performance difference of the models trained as training samples by different numbers of participating volunteers to infer the generalization capabilities of our system. Specifically, we use the collected data of 1 to 6 volunteers as training sample sets, and complete the training of these 6 sets of training sample sets with four classification models(KNN+RFE, LR+RFE, RF+RFE and SVM+RFE). Therefore, We obtained 24 fitted classification models. Finally, we will compare the performance of these 24 models by analyzing the performance of these classification models on the reserved unseen test data set.

Fig. 11 shows four different classification algorithms combined with our proposed DTW distance-based RFE algorithm. With only one volunteer data as the training data set, the F1 performance score of the worst performing model RF + RFE-Wdtw is still more than 0.96, and the other three models we optimized can even reach F1 scores above 0.98. In addition, except for the RF + RFE-Wdtw model, when the number of participants in the training sample data set is increased to 5, the performance has a significant fluctuation, the other three models are not sensitive to the impact of the number of participants in the training sample data set. Regardless of the number of participants in the training sample data set, the system performance of these three models is excellent, and can reach F1 scores above 0.98. Among them, the performance of the 2NN + RFE-Wdtw model is the most effective and reliable, because after the number of participants in the training sample data set is greater than or equal to 2, the model can stably reach an F1 score of 0.99 or more.

4.2.8. Comparison with existing approaches

We conduct a set of experiments to compare our system with recent existing approaches, i.e., UPR [24], in terms of recall and precision. UPR is based on geometrical characteristics of RSSI fluctuation and utilizes 3 rows and 3 columns topology tag array to detect falling movements. We set up the same scenario as in previous experiments and plot the results of two approaches in Fig. 12. The results show that the above two schemes involved in the comparison can achieve good performance on recall and precision indicators when there is only one volunteer. Specifically, the recall and precision of UPR even reached 100 percent when there is only one volunteer object, while our method achieved good results close to 99 percent. But when considering the impact of different volunteers, the recall and precision indicators of the UPR method will drop sharply (to 78.24% and 68.19%, respectively). The reason of such a decrease might be the deployment method of the UPR system, which stipulates that the tag array is deployed on the wall, and the volunteer's position is between the reader antenna and the tag array, resulting in that the extracted RF signal features in certain fall movements (e.g. No. 14 and 15 of Table 1) are very sensitive to different volunteers. However, a fall monitoring system, in practice, must have good generalization

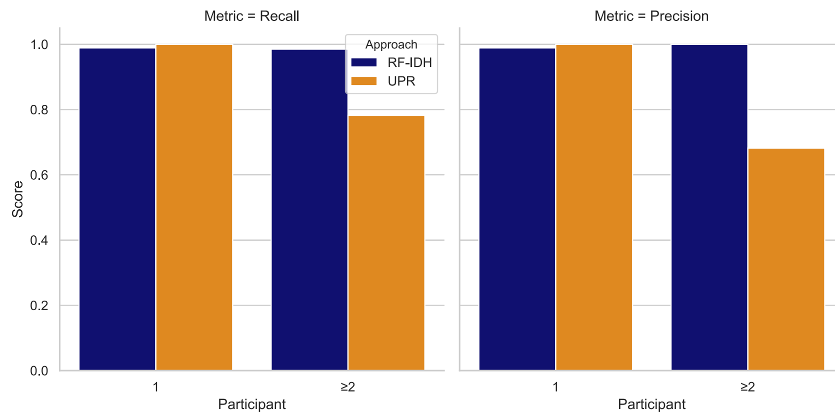


Fig. 12. Comparison with existing approaches.

ability and cannot be limited to monitoring a single hemodialysis patient. Compared with UPR, our RF-IDH can always achieve high recall and precision (say 98.51% and 100% on average) when more than one participant.

On the other hand, compared to the deployment method of UPR, our RF-IDH can avoid the negative impact of a humid environment on RFID passive tags. Besides, our system can further use the natural attribute EPC code of the RFID tag to establish an association with specific patients and cooperate with the basic disease information of the hemodialysis patients stored in the background, which can provide medical professionals with precautions for medical measures for falling patients. Therefore, the RF-IDH system we proposed is more practical than the existing UPR method and is more suitable for blood purification centers in hospitals.

5. Conclusion

In the context of smart healthcare and rehabilitation, meeting privacy requirements plays a vital role. Therefore, the IoT devices participating in patient monitoring must ensure that the collected data information is highly secure. Compared with image data, RF signal data is completely free from the risk of privacy leakage and can gain sufficient trust from users. However, using RF signal characteristics to interpret human activities is a challenging and rewarding task, especially for the IoT medical field. In this paper, the motivation for establishing an RF-IDH system is first described. Then, by analyzing the framework of the system and the working mechanism of internal components, we clearly show how to solve the multiple technical challenges step by step, including the RF bare signal preprocessing and the establishment of extraction algorithm for residual features based on hemodialysis patient safety process model. Finally, we implement our system on commercial off-the-shelf RFID devices and compared the evaluation metrics of the four methods of 2NN–RFE, LR–RFE, RF–RFE and SVM–RFE in terms of system performance, system efficiency, system robustness, and system latency. The evaluation results show that all models based on our proposed RFE algorithm have achieved good results and our RF-IDH that optimizes the 2NN–RFE method achieves excellent results than others. The results show that RF-IDH achieves a F1 score of more than 0.99 in both the cross-validation stage and the final test data evaluation stage. And as the training sample ratio increases, the evaluation metric approaches the maximum metric it can achieve. Moreover, the experiment results also show that RF-IDH is robust against the influence of individual diversity by different volunteers and has an acceptable fall recognition delay. This positive result inspires us to explore further real-world needs in the IoT medical field based on this high-performance, energy-efficient, low-cost RFID technology in our future work.

CRediT authorship contribution statement

Yi Chen conceived of the presented idea and contributed to the final manuscript. Fu Xiao was in charge of overall direction and planning. Haiping Huang discussed the experimental parts and polished English. Lijuan Sun proposed some suggestions about writing the manuscript.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] L. Xie, C. Wang, A.X. Liu, J. Sun, S. Lu, Multi-touch in the air: Concurrent micromovement recognition using RF signals, IEEE/ACM Trans. Netw. 26 (1) (2018) 231–244, http://dx.doi.org/10.1109/tnet.2017.2772781.

[2] Y. Zou, J. Xiao, J. Han, K. Wu, Y. Li, L.M. Ni, GRfid: A device-free RFID-based gesture recognition system, IEEE Trans. Mob. Comput. 16 (2) (2017) 381–393, http://dx.doi.org/10.1109/TMC.2016.2549518.

[3] L. Wang, T. Gu, X. Tao, J. Lu, Toward a wearable RFID system for real-time activity recognition using radio patterns, IEEE Trans. Mob. Comput. 16 (1) (2017) 228–242, http://dx.doi.org/10.1109/TMC.2016.2538230.

[4] Y. Bu, L. Xie, Y. Gong, C. Wang, L. Yang, J. Liu, S. Lu, RF-dial: An RFID-based 2D human-computer interaction via tag array, in: IEEE INFOCOM 2018 - IEEE Conference on Computer Communications, pp. 837–845, http://dx.doi.org/10.1109/INFOCOM.2018.8486309.

[5] Q. Lin, L. Yang, Y. Sun, T. Liu, X. Li, Y. Liu, Beyond one-dollar mouse: A battery-free device for 3D human-computer interaction via RFID tags, in: 2015 IEEE Conference on Computer Communications, INFOCOM, pp. 1661–1669, http://dx.doi.org/10.1109/INFOCOM.2015.7218546.

[6] C. Huang, L. Lee, C.C. Ho, L. Wu, Z. Lai, Real-time RFID indoor positioning system based on Kalman-filter drift removal and Heron-bilateration location estimation, IEEE Trans. Instrum. Meas. 64 (3) (2015) 728–739, http://dx.doi.org/10.1109/TIM.2014.2347691.

[7] P.C. Stan Salvador, FastDTW: Toward accurate dynamic time warping in linear time and space, Intell. Data Anal. 11 (5) (2007) 19.

[8] F. Merrouche, N. Baha, Depth camera based fall detection using human shape and movement, in: 2016 IEEE International Conference on Signal and Image Processing, ICSIP, pp. 586–590, http://dx.doi.org/10.1109/SIPROCESS.2016.7888330.

[9] B. Ni, C.D. Nguyen, P. Moulin, RGBD-camera based get-up event detection for hospital fall prevention, in: 2012 IEEE International Conference on Acoustics, Speech and Signal Processing, ICASSP, pp. 1405–1408, http://dx.doi.org/10.1109/ICASSP.2012.6287947.

[10] S. Zambanini, J. Machajdik, M. Kampel, Detecting falls at homes using a network of low-resolution cameras, in: Proceedings of the 10th IEEE International Conference on Information Technology and Applications in Biomedicine, pp. 1–4, http://dx.doi.org/10.1109/ITAB.2010.5687729.

[11] T. Zhang, W. Zhang, L. Qi, L. Zhang, Falling detection of lonely elderly people based on NAO humanoid robot, in: 2016 IEEE International Conference on Information and Automation, ICIA, pp. 31–36, http://dx.doi.org/10.1109/ICInfA.2016.7831793.

[12] S.A. Waheed, P.S.A. Khader, A Novel approach for smart and cost effective IoT based elderly fall detection system using Pi camera, in: 2017 IEEE International Conference on Computational Intelligence and Computing Research, ICCIC, pp. 1–4, http://dx.doi.org/10.1109/ICCIC.2017.8524486.
[13] P.S. Ong, C.P. Ooi, Y.C. Chang, E.K. Karuppiah, S.M. Tahir, An FPGA-based hardware implementation of visual based fall detection, in: 2014 IEEE Region 10 Symposium, pp. 397–402, http://dx.doi.org/10.1109/TENCONSpring.2014.6863065.
[14] R. Ramezani, Y. Xiao, A. Naeim, Sensing-Fi: Wi-Fi CSI and accelerometer fusion system for fall detection, in: 2018 IEEE EMBS International Conference on Biomedical and Health Informatics, BHI, pp. 402–405, http://dx.doi.org/10.1109/BHI.2018.8333453.
[15] A. Alesin, A. Osanlou, S.W. Maw, A low budget multifunctional wearable device for motion and falls detection, in: 2018 IEEE Conference of Russian Young Researchers in Electrical and Electronic Engineering, EIConRus, pp. 1850–1855, http://dx.doi.org/10.1109/EIConRus.2018.8317468.
[16] A. Wickramasinghe, D.C. Ranasinghe, C. Fumeaux, K.D. Hill, R. Visvanathan, Sequence learning with passive RFID sensors for real-time bed-egress recognition in older people, IEEE J. Biomed. Health Inform. 21 (4) (2017) 917–929, http://dx.doi.org/10.1109/Jbhi.2016.2576285.
[17] P. Wang, C.S. Chen, C.C. Chuan, Location-aware fall detection system for dementia care on nursing service in evergreen inn of Jianan hospital, in: 2016 IEEE 16th International Conference on Bioinformatics and Bioengineering, Bibe, 2016, pp. 309–315, http://dx.doi.org/10.1109/Bibe.2016.70.
[18] A. Wickramasinghe, D.C. Ranasinghe, Ambulatory monitoring using passive computational RFID sensors, IEEE Sens. J. 15 (10) (2015) 5859–5869, http://dx.doi.org/10.1109/Jsen.2015.2449862.
[19] J. He, C. Hu, Y. Li, An autonomous fall detection and alerting system based on mobile and ubiquitous computing, in: 2013 IEEE 10th International Conference on Ubiquitous Intelligence and Computing and 2013 IEEE 10th International Conference on Autonomic and Trusted Computing, pp. 539–543, http://dx.doi.org/10.1109/UIC-ATC.2013.54.
[20] D. Chen, W. Feng, Y. Zhang, X. Li, T. Wang, A wearable wireless fall detection system with accelerators, in: 2011 IEEE International Conference on Robotics and Biomimetics, pp. 2259–2263, http://dx.doi.org/10.1109/ROBIO.2011.6181634.
[21] B. Najafi, K. Aminian, A. Paraschiv-Ionescu, F. Loew, C.J. Bula, P. Robert, Ambulatory system for human motion analysis using a kinematic sensor: monitoring of daily physical activity in the elderly, IEEE Trans. Biomed. Eng. 50 (6) (2003) 711–723, http://dx.doi.org/10.1109/TBME.2003.812189.
[22] L.C. Zhu, R.C. Wang, Z.Q. Wang, H. Yang, TagCare: Using RFIDs to monitor the status of the elderly living alone, IEEE Access 5 (2017) 11364–11373, http://dx.doi.org/10.1109/Access.2017.2716359.
[23] W. Cao, X. Liu, F. Li, Robust device-free fall detection using fine-grained Wi-Fi signatures, in: 2017 IEEE 2nd Advanced Information Technology, Electronic and Automation Control Conference, IAEAC, pp. 1404–1408, http://dx.doi.org/10.1109/IAEAC.2017.8054245.
[24] L. Yao, Q.Z. Sheng, W.J. Ruan, X. Li, S. Wang, Z. Yang, Unobtrusive posture recognition via online learning of multi-dimensional RFID received signal strength, Icpads, 2015 Ieee 21st International Conference on Parallel and Distributed Systems (2015) 116–123, http://dx.doi.org/10.1109/Icpads.2015.23.
[25] A.H. Fakhrulddin, X. Fei, H.C. Li, Convolutional neural networks (CNN) based human fall detection on body sensor networks (BSN) sensor data, in: 2017 4th International Conference on Systems and Informatics, Icsai, 2017, pp. 1461–1465.
[26] G.B. Hu, X.S. Qiu, L.M. Meng, RTagCare: deep human activity recognition powered by passive computational RFID sensors, in: 2016 18th Asia-Pacific Network Operations and Management Symposium, Apnoms, 2016.
[27] R.L.S. Torres, A. Wickramasinghe, V.N. Pham, D.C. Ranasinghe, What if your floor could tell someone you fell? A device free fall detection method, in: Artificial Intelligence in Medicine, Vol. 9105, Aime 2015, 2015, pp. 86–95, http://dx.doi.org/10.1007/978-3-319-19551-3_10.
[28] ImpinJ., Speedway revolution reader application note: Low level user data support, 2010, [Online]. Available: http://www.impinj.com. Speedway Revolution Reader Application Note.

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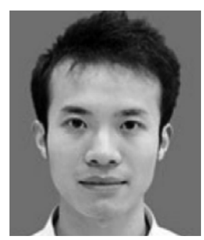

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