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Optimized Algorithm for RFID-Based Activity Recognition of the Elderly

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ABSTRACT As the trend toward an increasingly aging global population accelerates, more attention is being focused on healthcare services for the elderly. Traditional healthcare services for the elderly require personal, meticulous care. With increasing numbers of the elderly and the ''inverted pyramid'' of family structure, more and more elderly people are often unable to obtain the healthcare they need in their final years. This paper introduces a Densely Convolutional Network for optimizing the algorithm model of an RFID-based activity recognition system, leading to a more accurate analysis of the basic daily behaviors of the elderly.During the experiment, We also optimized the original recognition process from combination of a series object-use recognition to treating multiple object-use processes as a union process.Which improves the efficiency and speed of activity recognition.

INDEX TERMS Activity recognition, deep learning, healthcare, passive RFID.

I. INTRODUCTION

Healthcare for the elderly is an increasingly significant societal issue. When the elderly are left alone, there is often a high incidence of accidents. A more effective method for monitoring the elderly could prevent many such accidents. In a senior care facility, the staff usually needs to take care of many residents at the same time, and if there is an emergency, such as a fall or sudden illness, a staff person may not be immediately available, possibly resulting in the situation being made worse, or even death [2], [4]. There are currently three main types of intelligent monitoring methods. The first is wearable monitoring equipment for the staff, along with corresponding equipment for the residents. However, this equipment must be recharged for the next use [1] and, in addition, is neither a truly smart nor user-friendly solution. The second method is to use a video camera to observe the activities of the elderly through computer vision recognition technology, which can send an alert to whoever is on duty if an issue occurs. The problem with this method is that it can be an invasion of privacy and is not a good choice in certain situations [3], [5], [6]. The third method is to monitor activity by an infrared or Bluetooth device. The problem with this approach is that it is expensive and may not be applicable to a family or organization [7], [8].

This paper presents a method of activity recognition based on the use of low-cost RFID tags and machine learning. This method changes the existing RFID-based activity recognition method, which uses either a received signal strength (RSS) signal or a phase signal, and improves the accuracy of activity identification. The activity recognition method based on RSS primarily uses the change in the wireless signal caused by the activity to recognize the activity [10]. However, because RSS is susceptible to signal noise, the RSS-based activity recognition method can only achieve 56%–72% accuracy. This makes it difficult to accurately identify specific activities simply by using the fluctuation of signal intensity over time. For example, the accuracy of the methods mentioned by Sigg [11] is only 56%. Kodeswaran et al. used radio software devices to increase the accuracy of RSS to 72% [12].

This paper is based on the experimental methods and research results of Ivan Marsic et al. This paper introduces the densely convolutional network (DenseNet), which is optimized from a convolutional neural network (CNN). DenseNet's dense connections can alleviate the problem of gradient disappearance, enhance feature propagation, encourage feature reuse, and greatly reduce the number of parameters. Through an experiment in identifying the activities of daily living (ADL) of the elderly, we found that our

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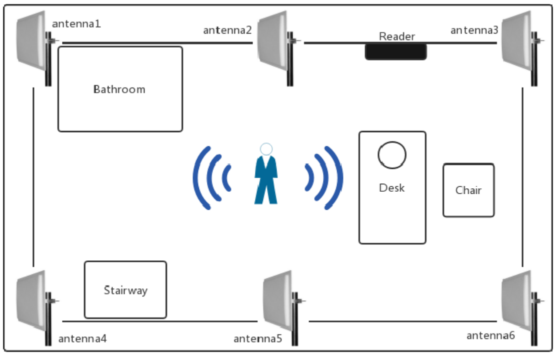

FIGURE 1. Placement of the radio frequency identification antennas.

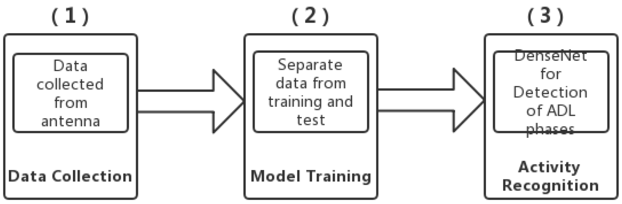

FIGURE 2. Activity recognition system diagram.

TABLE 1. List of tagged objects, number of tags, and activity involving the object.

Object(# of tags)	Activity
Chair (5)	Sit/Bed-Chair Shift
Soup ladle (2)	Eating
Chopsticks (2)	Eating
Zipper clothing (5)	Getting dressed
Trousers (5)	Getting dressed
Towel(2)	Taking a bath
Toilet paper (inside) (2)	Using paper
Desk (2)	Eating
Bed (2)	Shifting from Bed to Chair
Soap (1)	Eating
Toothbrush (1)	Brushing Teeth

RFID-based model achieved 81% accuracy. At the same time, we designed and optimized the relevant experimental steps and activity verification methods. Finally, we summarize and analyze the advantages and limitations of RFID technology in activity recognition and give our views on future developments.

II. RELATED WORK

Our experiment was carried out in a senior care facility. We chose one of the living rooms as the experiment's site. We deployed six RFID antennas and two readers on four sides of the room, as shown in Fig. 1. The reading range was 3–4 m to collect data transmitted by RFID tags. Since the movement of label objects can be calculated by RSSI fluctuations, we filter the collected data and divide the data into training data and test data [7], [13], [14]. The training data are used to train our DenseNet deep learning network, and the test data are used to test the effect of our learning. Through repeated experiments and tests, we were able to obtain a relatively stable DenseNet.

We used the Model ALR-9900+ RFID reader from Alien Technology [15]. We installed two readers in the living room, hidden in a space above the ceiling. Antennas 1–3 were connected to Card Reader 1, and antennas 4–6 were connected to Card Reader 2. These connections allowed simultaneous activation of a pair of antennas: 1 and 4, 2 and 5, and 3 and 6 in turn [14], [16].

The type and location of RFID tags were determined by the composition and size of objects and their usage patterns [17]. We evaluated several tag configurations for each of these factors and selected configurations for each object that produced the highest RFID readout rate.

1) Label type: We chose the type of label according to the material of the object. Passive RFID tags do not perform well when they are connected to metal surfaces or liquid containers. We put hard metal labels on metal objects such as spoons. Although these special tags are expensive, they can be reused. Liquid containers (e.g., water bottles) and objects in aluminium packaging (e.g., bags of sugar) were labeled with conventional labels to minimize contact with the liquids or aluminium.
2) Number and location of tags: For each object, we identified surfaces that could be used for marking and selection.. Surface availability depends on four factors: item protection (for objects with strict hygiene requirements, only packaging surface can be marked); shape constraint (flat surfaces were preferred, as tag folding degrades performance); smoothness (tags adhere better to smooth surfaces); and size (most objects were marked with two RFID tags, for better detection if one label is unreadable, the Other tags are still readable).

As shown in Table 1, we used 29 passive RFID tags to mark 11 objects of 19 types. Tagged objects included spoons, towels, and chairs. Observing the daily lives of the elderly, we have noticed that some tags cannot be detected (such as clothes hanging on a stool), because these tags are small and fold around the shape of the object. In these cases, if the initial tag did not interfere with the use of the object, we replaced it with a larger tag. If a larger label was not feasible, we kept the small label but relocated it to improve its detection rate.

III. ACTIVITY RECOGNITION

Activity recognition is an area of much research [19], and many researchers have explored approaches for activity recognition algorithms. Sensor-based methods are increasingly used in human activity recognition. Although simple activities can be identified by body sensors, complex activities require additional cues, such as body position, speech, or objects in use [18], [20], [21].

RFID technology can achieve high-precision interactive detection, but it has limitations. First, it requires human participation, which can be disruptive in practical applications. Even in a relaxed home environment, participants must wear or grab objects with an unarmed hand [22], [23]. Second, in the course of conducting several long-term experiments, it was found that near-field communication (NFC) is not feasible, because they may affect the activities of human beings. This restriction affected our work because we were continually running experiments and collecting data in actual living rooms, rather than performing a few experiments in a laboratory environment. To ensure that intrusion was kept to a minimum, we used deployment and evaluation methods developed in our early work to design our tagging methods in the living room and RFID antenna settings [24]. Finally, the signle reader provides binary detection information rather than signal strength values. Although the received signal strength indication (RSSI) of passive radio frequency identification (PRID) often has noise interference, it contains an abundant amount of information that can be extracted by using multiple readers and data processing techniques.

IV. DATA COLLECTION

The experiment was carried out in a senior living community institution. We installed hardware for RFID data collection and system activation control in the actual living room. Two Speedway R420 (8-port) RFID readers from Inpinj Inc. were used to collect RFID data and to record the RFID data in Max Miller mode and dual-target search mode [25]. We analyzed the data by recording the specific daily activities of individual elderly people in the living room. We developed a fully automated system that was activated every morning when the elderly woke up and recorded all the tags' RFID data during the activity. We set up a Microsoft Kinect for Windows V2 sensor to monitor the number of people in the room [26]. When there was only one person in the room, the RFID system was activated to record data. In order to identify ten basic daily activities (as shown in Table 1), we tagged several objects that need to be used in daily life according to existing tagging strategies. Different objects may use more than one tag, because objects in specific use scenarios help us to detect RSS signals. The system records the RSS from tags in this format during the daily activities of the elderly: [timestamp, tag ID, RSS, card reader name, port number].

Aside from RSS, the attributes of RFID signals, such as Doppler shift and phase angle, have been used for human-object interaction detection or human tracking. Our experience with these demonstrated that the Doppler shift measured by the Inpinj Speedway R420 reader API was not sufficiently accurate for our purposes.

TABLE 2. Activities used in this paper and their ADL codes.

Activity	Code	Activity	Code
Eating	E	Urinary Control	UC
Taking a Bath	TB	Toilet Control	TC
Brushing Teeth	BT	Bed-Chair Shift	BCS
Getting Dressed	GD	Walking	W

A. DENSENET MODEL

DenseNet is a CNN with dense connections. In this network, there is a direct connection between any two layers, that is to say, the input of each layer of the network is the union of the output of all the previous layers, and the feature maps learned by this layer will be passed directly to all the layers behind it as input. Fig. 1 shows the Dense Blocks of DenseNet. The blocks' structure is as follows: BN-ReLU-Conv (1*1)–BN-ReLU-Conv (3*3).

A DenseNet consists of several such blocks. The layer between each Dense Block is called a transition layer, which consists of BN>Conv(1*1)>average Pooling(2*2). Dense connections greatly increase the number of network parameters and the speed of computation, making DenseNet more efficient than other neural networks, due to a reduced computing load and the ability to reuse features in each layer of the network. DenseNet lets the input of layer L directly affect all subsequent layers, and its output is XL = Hl ([X0, X1,... (xl_1]), where [x0, x1,..., xl_1] merges previous feature maps in channel dimensions. Since each layer contains the output information of all previous layers, it only needs a few feature maps, which is why there are fewer parameters in DenseNet than in other CNN models. Generally speaking, DenseNet, as a CNN with deeper layers, has fewer parameters than a residual neural network (ResNet). Meanwhile, bypass enhances the reuse of features, makes the network easier to train, has a certain regularization effect, and alleviates the problems of vanishing gradients and model degradation.

B. DENSE CONNECTIVITY

We know that the structure of ResNet can be described as Xl = Hl (Xl-1) + Xl-1. Xl denotes feature maps generated by the lth layer, while Hl denotes corresponding calculations on the lth layer (generally, BN+ReLU+Conv, etc.). Accordingly, DenseNet's network structure can be described as Xl = Hl ([X0, X1,..., Xl-1]), where [X0, X1,..., Xl-1] represents the set of feature maps generated by the previous layers, which are the same as the lth layer feature map size. Compared with ResNet, DenseNet uses not only the input of the previous layer as the input of the successor layer but also

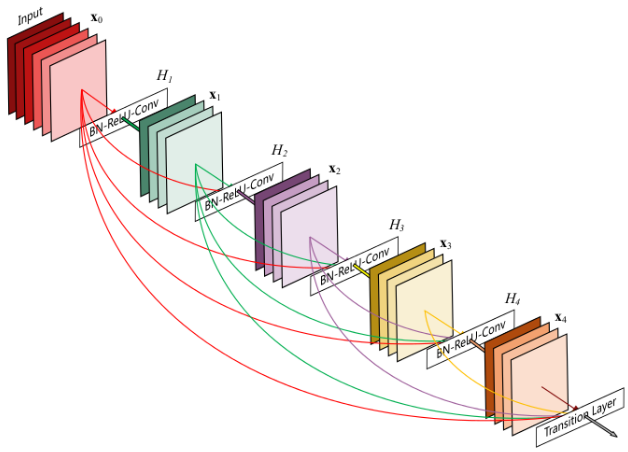

FIGURE 3. A five-layer dense block with a growth rate of k = 4. Each layer takes all preceding feature-maps as input.

all the layers with the same features as its. In addition, unlike ResNet, DenseNet does not add these prelayers as input but propagates them backward by direct simple concatenation.

C. GROWTH RATE

DenseNet's design does not need to be very wide (i.e., there are not too many trainable parameters for each layer) because it can better reuse features between layers. In our experiment, if each layer produces k output feature maps, then the input feature maps corresponding to the lth layer (Hl) should be K0 + (l-1) * K. Here, K0 corresponds to the input feature map channels of the input layer, so we set K = 12. Here, k, also known as growth rate, determines how many fresh features each layer can add to the global feature set.

D. BOTTLENECK LAYER

Although each layer in DenseNet blocks produces only K feature map output, it has a good deal of feature map input. For this reason, in ResNet/Inception series/SqueezeNet and other networks, in our experiment we introduced a bottleneck layer of 1 × 1 Conv before each 3 × 3 Conv operation, effectively limiting the number of input feature maps to a reasonable range. So the real calculation (Hl) of each layer is BN-ReLU-Conv (1 × 1) - BN-ReLU-Conv (3 × 3).

E. TRANSITION LAYERS

Because every conv_block in a dense block increases the growth_rate feature map, it is necessary to add transition layers after a dense block, in order to compress a certain number of feature maps and thereby ensure the efficiency of training.

F. MODEL TRAINING

We trained two DenseNets to detect five process stages and ten daily activities using a three-week preprocessing of the daily activities in the living room. Labels of data per second (one of five process stages or ten activities) were manually generated by paramedics according to the corresponding behavioral activity video review. Because each subject's body and living habits are different, and the duration of each activity is unpredictable, some of the ten activities are not well displayed. This is different from the five behavior stages, these stages are well performed [27]. In the case of unbalanced datasets, random selection of sample size does not guarantee sufficient data for all activity classes during training and testing. We selected a percentage of data from each class for training and used the remainder for testing.

TABLE 3. Confusion matrix for five ADL phases.

	PA	IP	A	SA	PSA
PA	67.98%	2.78%	5.97%	8.97%	3.21%
IP	26.98%	89.19%	12.87%	11.89%	9.86%
A	3.78%	4.78%	78.91%	11.27%	2.35%
SA	12.91%	3.98%	1.23%	79.23%	0.12%
PSA	11.38%	7.11%	3.67%	0.97%	67.91%

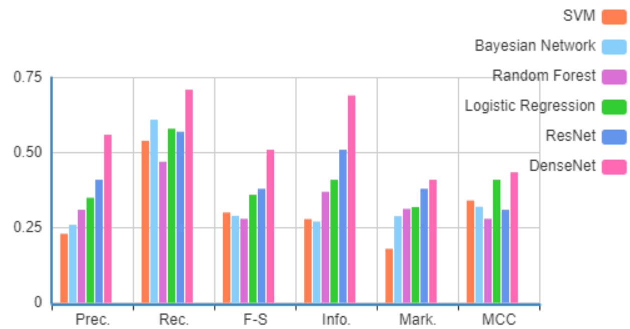

FIGURE 4. Performance comparison using different classifiers to predict ADL phases.

V. RESULTS AND ANALYSIS

First, we applied DenseNet to detect five stages of daily life behavior: pre-action (PA), in-position (IP), primary action (A), secondary action (SA), and post-secondary action (PSA). Phase detection was a challenge because the process phases are a high-level concept that are defined using lower-level concepts, such as objects used or constituent activities [28]. We preprocessed all recorded RFID data and randomly selected 3 h from each stage as training data and used the remaining data for testing. This meant that less than 50% of the total data were used for training. We used the TensorFlow open-source platform to train our DenseNet and stopped training when the cross-validation error remained unchanged for a period of time. The average detection accuracy of the system for five phases was 76.84%.

We compared the performance of DenseNet with the commonly used classifiers and CNN: one for all support vector machines (SVMs), one for all logistic regression, random forest, and Bayesian networks, using the previously introduced features on the same dataset. We regarded the phase detection as a multi-class classification problem and the phase detection of each process as a binary classification

TABLE 4. Confusion matrix for recognition of ten ADL activities. "OT" for activity other than selected nine activities.

	OT	E	TB	BT	GD	SC	UC	TC	BCS	W	UDS
OT	73.19%	12.80%	1.78%	3.28%	28.91%	9.88%	3.11%	0.91%	11.70%	0.91%	0.06%
E	18.91%	96.31%	46.91%	0.81%	0.01%	0.01%	0.03%	1.31%	0.01%	1.26%	0.01%
TB	16.13%	67.74%	61.92%	0.96%	0.03%	0.02%	0.13%	3.12%	0.01%	0.00%	0.03%
BT	31.28%	1.53%	8.91%	52.69%	0.01%	0.01%	1.52%	1.56%	0.03%	0.00%	0.21%
GD	7.91%	0.91%	21.81%	0.16%	81.34%	0.04%	0.13%	0.01%	0.01%	0.16%	0.05%
SC	7.30%	0.87%	1.27%	0.00%	0.00%	63.78%	0.05%	0.01%	0.86%	0.01%	0.01%
UC	4.51%	0.86%	1.31%	0.00%	0.00%	67.8	32.56%	0.01%	0.01%	0.01%	0.01%
TC	3.28%	0.00%	0.98%	0.01%	0.01%	0.01%	0.01%	11.78%	0.01%	0.01%	0.00%
BCS	7.56%	0.00%	0.01%	0.01%	0.01%	0.01%	0.01%	0.01%	67.91%	0.01%	1.28%
W	3.98%	0.56%	8.99%	7.13%	2.91%	0.06%	0.08%	0.17%	21.88%	97.32%	3.78%
UDS	4.67%	0.00%	0.01%	0.00%	0.02%	0.02%	0.00%	0.03%	0.13%	1.25%	76.45%

problem. We used F-scores, informativeness, markup, and Matthew correlation coefficient (MCC) [29] as common indicators. As can be seen in Fig. 4, the results demonstrated that our DenseNet achieved the highest performance, including a 15% performance gain compared with ResNet (which had the second highest classifier performance in Fig. 4).

VI. CONCLUSION AND FUTURE WORK

This research offers two main contributions. The first is the creative application of DenseNet to the field of activity recognition. This model is a method of activity recognition using passive RFID devices. Its recognition accuracy demonstrates obvious improvement compared with the traditional method of using RSS only or object-use combined with a classifier. The second contribution is the use of DenseNet, based on a CNN algorithm, to match features, which improves the accuracy of activity recognition. Through cross-testing in several experimental environments, the average recognition accuracy reached 82.78%, which we believe proves the effectiveness of this method.

We have identified some problems during the experiment we did, which needed to go deeper to research in future work. First, the complex activity recognition issue. We have many complex activities which may be formed of sub-activity. e.g. Think about the activity a man who has some problem with his legs may using a crutch to walk with. Which is consist of two sub-activities: Walking and Using a Crutch. The process of recognition will take more time than handling two independent sub-activities. The more complex the activity is, the more cost will have. This issue will have a great impact on us. Second, Speed and efficiency of recognition. In actual application scenarios, the sooner you discover a problem with the elderly's behavior, the more we can prove the value of our research. Therefore, in the following research, the recognition of complex activities, speed, and accuracy are the main directions.

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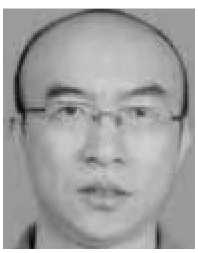

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