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Elderly Fall Detection Method Using Threshold Based Method and Transfer Learning

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Abstract. The lack of elderly data is one of the most challenging issues in elderly fall detection. And the simulated young data is usually used in fall detection researches. In this paper, a wearable elderly fall detection method based on threshold based method (TBM) and transfer learning is proposed to shorten the distribution difference between young data and elderly data. In the process of training, labeled young data (source domain) and unlabeled elderly data (target domain) are utilized so as to weak the adverse effects of distribution difference between young data and elderly data. Finally, the better performance with sensitivity 98.63% and specificity 98.00% is illustrated with elderly data in Sisfall dataset.

Keywords. Fall detection; wearable; Transfer learning; Threshold Based Method; power consumption

1. Introduction

Falls are an important public health problem worldwide. It is reported fatal falls occur about 646,000 times a year, making it the second leading cause of unintentional injury death after road traffic injuries[1]. And falls cause direct and indirect injuries. Half of fall injuries are fractures, and more than 95% fractures of the hip are caused by fall. Frailty increases with age, and older people spend much longer in the hospital because of falls than others, even staying in the hospital all the time. In addition to physical harm, fall will also cause psychological damage, including fearing to fall again, loss of independence, messy mind, loss of confidence and depression, etc[2]. As a result, the confidence of living independently and participating in social activities is reduced, which would increase the gerontal weakness and reduce their quality of life. So it is necessary to develop an elderly fall detection system to monitor their activity, and notifying guardian in case of falls.

Fall detection methods can be divided into three categories according to the types of sensors: visual-based fall detection method, environmental-based fall detection method and wearable-based fall detection method The first two categories require to deploy the sensors such as depth cameras, pressure sensors and/or infrared sensors in elderly's living area. They distinguish between falls and activities of daily living (ADLs) by

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analyzing body posture changes and/or environmental information within a specific range. However, both methods have the disadvantages such as limited to a particular room, expensive cost and/or the privacy issue of the elderly. In recent years, wearable fall detection method has become one of the research hotpots in the field of elderly fall detection. They usually utilize wearable devices embedded with accelerometer, gyroscope, magnetometer, and/or pressure sensor on the body to collect human movement information, so as to distinguish fall from ADLs. In conclusion, compared with the first two categories fall detection methods, the wearable-based fall detection method have the advantages of low cost, less privacy issues and available anywhere.

Wang et al.[3] proposed a TBM based low-power fall detector : NEON. In this paper, simple TBM is used to classify signals detected by accelerometers and baroceptor. Finally, the NEON's power consumption is effectively reduced and the service life of the device is extremely extended. However, the performance of TBM is limited, and it cannot balance the sensitivity and specificity well. As a result, the sensitivity reached only 91%. Abdulaziz et al.[4] proposed a fall detection system based on Killer Heuristic Optimized Convolution neural network. The fall detection system transmits the extracted features to a better processor via Radio Frequency signals. Sophisticated ML algorithms are used to distinguish falls from ADLs, and ultimately improving the accuracy to 99.45%. However, the high power consumption of real-time data transmission leads to reduced service life of the device.

In this paper, an elderly fall detection method with low power consumption is proposed in this paper. The TBM and transfer learning (TL) based fall detection algorithm is applied to detect the fall of elderly. In this method, TBM with computing simple features is deployed in wearable device (SNFD) to preliminarily classify part of ADLs and basically all fall events (suspected falls). Finally, the power consumption is decreased because the transmission data is reduced. To minimize the distribution difference between the elderly data and the young data, the TL is trained by the labeled young data and unlabeled elderly data. As a result, TL is applied on the cloud platform to further classify the suspected falls and improve the performance of the elderly fall detection algorithm.

2. Snfd Design

A typical fall process can be divided into four phases (pre-fall, weightless, impact and static). In the pre-fall stage, the human body is in normal activity. In the weightless stage, the body would suddenly move towards the ground. In the impact stage, the body collide with the ground. In the static stage, the human lie on the ground and keep static. In proposed TBM, the last three stage is used to identify falls and ADLs. The first step of TBM is performed using the free fall interruption inside the MPU6050. The second step is realized in MSP430F149, a 3s data window is captured, and the software program in the microcontroller is run to identify whether a suspected fall has occurred. If it has occurred, the 3s data window is uploaded to the cloud platform. Once the whole processing is done, the SNFD goes into low-power mode until the free-fall interrupt is triggered again.

Feature selection plays an important role. Its purpose is to select the parameters (features) that can distinguish falls and ADLs from the original data, and finally these features are used to determine whether falls occur. $a_x[i]$, $a_y[i]$ and $a_z[i]$ are the i th acceleration samples of the triaxial accelerometer along the x, y and z-axes, respectively.

The mean value of a_y ($\overline{a_y}$) can characterize the static phase of a fall. When the elderly stands, the y-axis is parallel to the direction of gravity ($\overline{a_y} \approx 1\,g$). When the elderly is lying down, the y-axis is perpendicular to the direction of gravity ($\overline{a_y} \approx 0\,\mathrm{g}$). The minimum value of maximum value of absolute value of triaxial acceleration (MAV_{min}) and its maximum value (MAV_{max}) of MAV can also capture weightlessness and impact stage of fall, respectively. As shown in figure 1, all these three features can identify falls from ADLs.

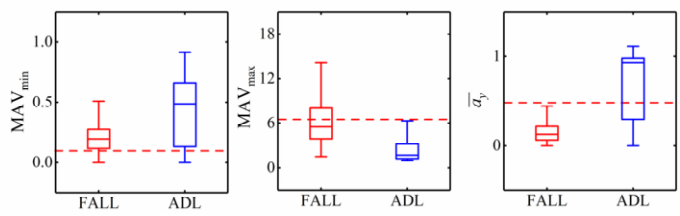

Figure 1. Box diagram of MAVmax, MAVmin, and $\overline{a_y}$

The TBM phase includes 5 parts, which are (1) interrupt triggering, (2) signal acquisition, (3) feature extraction, (4) event classification, and (5) data transmission. (Fig.2)

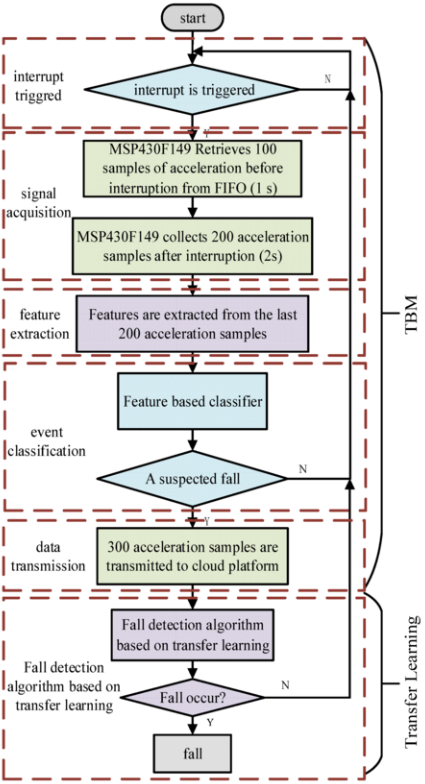

Figure 2. Flow chart of elderly fall detection algorithm.

In the interrupt trigger program, the SNFD enables the FIFO and free fall interrupt of the MPU6050, while the MSP430F149 is configured to operate in sleep state (LPM_3) and BC26 in PSM mode to save battery power. At this point, SNFD only uses MPU6050 to collect acceleration samples and store them in FIFO. When the MPU6050 captures a sudden movement of the human body(weightless), its internal free fall interrupt will be triggered. The triggering condition of the free fall interruption is: the MAV is less than the threshold th_0.

After the data acquisition program, features are extracted from DW_2 and DW_3 for subsequent event classifiers. comparing those features with preset thresholds. If both the features exceed the corresponding thresholds, the current event is classified as a suspected fall event, and SNFD transmits a time series of 300 triaxial accelerations to the cloud platform via BC26.Otherwise, the current event is classified as ADLs and an interrupt trigger is returned.

3. Fall Detection Algorithm Based on Transfer Learning

The data collected by the accelerometer are continuous triaxial acceleration data changing with time. Taking raw data directly as input ignores the data relationship between *x*, *y*, and *z* axes. Therefore, the time series data of *x*, *y*, and *z* axes are converted into images in this paper, and the transfer learning algorithm with Convolutional Neural Network is used to classify the images, so as to better mine the correlation between data of different axes.

Firstly, the 3s data window of suspected fall events was intercepted from the original human activity signal according to the TBM. The 3s data window is composed of the acceleration time series for *x*, *y*, and *z* axes, each axis contains 300 acceleration sample points (value range is [-16g, 16g]). The acceleration value of *x*, *y* and *z* axes at different time can correspond to the color of corresponding position of the image. Finally, the processed data is converted into an image. From the image can see that the changing rules of falls and ADLs are different, so the encoded image can be used for final classification.

At present, the main data sources of fall detection algorithms are young's falls and ADLs. Obviously, elderly have different behavior habits with younger people, and the cost of a fall is unaffordable for elderly. It can be seen that There were differences in the distribution of original data on falls and ADLs among young and elderly people. Therefore, it is necessary to optimize the fall detection algorithm based on the existing few elderly fall events. The transfer learning algorithm can transfer the prior knowledge learned from the data of young to train a new fall detection algorithm suitable for the elderly by using limited fall samples of the elderly. So transfer learning is applied in this paper to recognize fall and ADLs. In the training process, a large number of young's ADLs and fall images and labels is used as the source domain, and the elderly's ADLs images and limited elderly fall images is adopted as the target domain. the training data of source domain and target domain is denoted as $X_s = [x_s^1, ..., x_s^{n_s}] \in \Re^{D \times n_s}$ and $X_t = [x_t^1, ..., x_t^{n_t}] \in \Re^{D \times n_t}$ (D is the dimensionality, and ns and nt are the number of training samples in source and target domains.), respectivily. For X_s, its corresponding label is $T_s = [t_s^1, ..., t_s^{n_s}]^T \in \Re^{n_s}$. For the testing process, the X_t is applied to test the performance of the proposed algorithm.

Domain adaptive Neural Network (DaNN)[5] is a type of transfer learning, which is often used to recognize images. In this study, the fall detection algorithm based on DaNN is applied to classify fall and ADLs, and the training model is shown as Fig.3. This model is organized by feature extraction(the green dotted box in Fig.3) and event classification(fully-connection2). Furthermore, maximum mean difference based on the Gaussian kernel (*MMD*) is used to judge the proximity extend of the probability distribution between source domain and target domain. *MMD* is defined as follow:

$$MMD(X_s, X_t) = \left\| \frac{1}{n_s} \sum_{i=1}^{n_s} f(x_s^i) - \frac{1}{n_t} \sum_{i=1}^{n_t} f(x_t^i) \right\|_H^2 \tag{1}$$

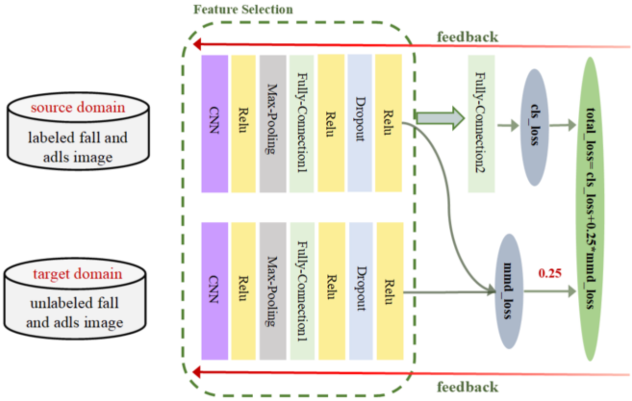

Figure 3. Training model of transfer learning algorithm.

Where H represents the distance, which is measured by the data $f(x)$ mapping to the reproducing kernel Hilbert space (RKHS). In this paper, Gaussian Kernel Function is used as $f(x)$. Its calculation is as follows:

$$k(x, x') = e^{\frac{-\|x-x'\|^2}{2\sigma^2}} \tag{2}$$

Where σ is the bandwidth, controlling the radial range of action, and it is set as a large value. The reason for choosing a Gaussian kernel is that it can map data to infinite dimensional space. Then, *MMD* is used as regularization embedded in supervised back-propagation training. By using the regularized training network parameters, the target domain can be optimized in supervised training and the hidden layer can remain unchanged between different domains. Cross-Entropy-Loss function (*CLS*) is used to judge the proximity between the actual output (T_o) and the target value(T_s). CLS is defined as follow:

$$CLS(T_o, T_s) = \sum_{i=1}^{n_t} T_o(t_i) \log \frac{1}{T_s} = -\sum_{i=1}^{n_t} T_o(t_i) \log T_s \tag{3}$$

Finally, total_loss of the proposed algorithm is consisted of cls_loss and mmd_loss. The function of total_loss is calculated as follow:

$$total\_loss = cls\_loss + \lambda * mmd\_loss \tag{4}$$

λ is domain regularization parameter.

The training process can be divided into initialize network parameters with small random numbers; *MMD*_loss and *CLS*_loss are calculated by forward network; Updating network parameters by back-propagation, the calculation formula is as follows:

$$\theta(t) = \theta(t-1) - \alpha \frac{\partial total\_loss}{\partial \theta(t-1)} \tag{5}$$

4. Experiments

The training data and testing data used in this research are derived from the public data set Sisfall. In this chapter, we use this data set to train and test TBM and TL algorithm. Particle swarm optimization (PSO) algorithm is used to find the optimal threshold of TBM, which can reduce the data uploaded to the cloud platform. For TL algorithm, different parameters are selected to find the best fall detection algorithm model, so as to improve the performance of the elderly fall detection algorithm.

In TBM, young data(1723 sets of falls and 1808 sets of ADLs) is used as the training data. BC26 generates a large current when transmitting data, so the less data the SNFD uploads, the longer its service life. Therefore, uploading the least suspected fall events while uploading basicly all falls can effectively save power (*Spc* was highest when the *Sen* was nearly 100%). The result shows that 83.32% ADLs can be discards when *Sen* is 99.65%. Therefore, the sleep duration of microcontroller is extended because of the working of free-fall interrupt. Then, 964 sets of elderly data samples (73 falls and 891 ADLs) were used to test the performance of TBM. 231 suspected fall events (73 falls and 158 ADLs) were uploaded and reject 733 ADLs. As a result, TBM achieves a *Sen* of 100%, a *Spc* of 82.27% and an *Acc* of 83.60% during the test. In the ML stage, the suspected fall data windows captured in the training of TBM were encoded as images. And its labels and images were used as the source domain of the TL. The suspected fall data windows captured during the test of TBM were encoded as images, and it is used as the target domain of the TL.

In order to test the performance of TL, 231 suspected fall images in the target domain were used as test data. It can be seen that the optimal sensitivity of TL was 98.63%. Meanwhile, the best specificity was over 92% when $\lambda = 0.4$. As a result, the *Sen* of TL achieves 98.63% (72 falls are correctly classified), the *Spc* is 92.41% (146 ADLs are correctly classified), and the *Acc* is 94.27% (218 samples are correctly classified). Finally, the whole fall detection algorithm (TBM + TL) achieves a *Sen* of 98.63% (72 falls are correctly classified), a *Spc* of 98.65% (879 ADLs are correctly classified), and an *Acc* of 98.65% (951 samples are correctly classified).

Current fall detection algorithms are mainly divided into two categories: TBM and machine learning. TBM can greatly reduce the power consumption of the device, but the performance is low. Wang [6] proposed a TBM method to distinguish falls from ADLs so that the service life of Fall Detector was extended greatly. However, its sensitivity and specificity were only 93.0% and 89.3%. Therefore, many researchers use machine learning algorithms with better classification performance to detect falls. In [7], four different machine learning algorithms are used to distinguish falls from ADLs, and all of them achieve better performance than TBM proposed by Wang et al. In this paper, the proposed elderly fall detection algorithm uses TBM to reduce the power consumption and improves the performance of the algorithm by TL algorithm, and the sensitivity, specificity and accuracy reach 98.63%, 98% and 98%.

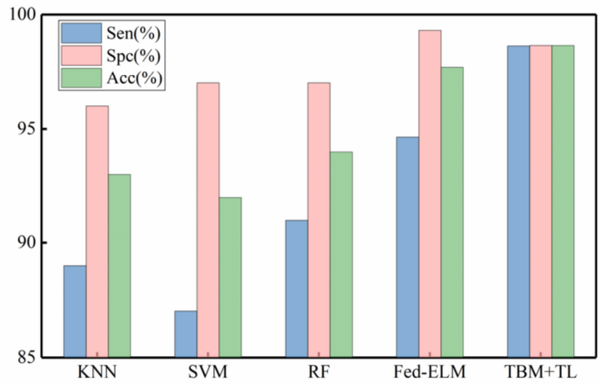

Figure 4. Performance of different elderly fall detection algorithms on Sisfall

Furthermore, there are also some studies using Sisfall dataset to detect falls of the elderly, such as [8] and [9]. In [8], Support Vector Machine (SVM), K-Nearest Neighbor (KNN) and Random Forest (RF) are used to detect the fall of the elderly, but it does not consider the low performance of the fall detection model caused by the inconsistent data distribution of young and elderly. And in [9], a small amount of elderly users' own data are used to improve the performance of the elderly fall detection algorithm, but it cannot solve the problem of inconsistent data distribution among young and elderly. The method proposed in this paper uses MMD to shorten the distribution distance of the data of young and old people at the feature level, so as to improve the accuracy of detecting the elderly fall events. And the Fig.4 shows the performance comparison of several algorithms to distinguish falls and ADLs of the elderly in the Sisfall dataset. Among several methods, it can be seen that the sensitivity and accuracy of TBM+TL proposed in this paper are the best.

5. Conclusion

In this paper, the TBM-TL elderly fall detection method can effectively reduce the power consumption of the wearable devices while improving the classification performance. In wearable device, the hardware and software is combined to reduce its power consumption. The hardware with low power characters are select to decrease the power consumption, and they are in the lowest power condition by the controlling of software. And the TL algorithm trained with labeled youth data and limited unlabeled elderly data can distinguish falls and daily activities of the elderly well. Finally, proposed elderly fall detection method achieves satisfactory results in power consumption and algorithm performance.

In the future, real-world elderly fall and ADLs is considered to be collected in safe condition. And the collected data would be used for the study of fall detection method.

In addition, the algorithm that can be updated in the process of applying would be focused. For low power consumption, the effect of low sampling rate and short upload data window on the performance of elderly fall detection algorithm is worth discussing.

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