노인 홈 케어를위한 CNN 기반의 비정상 인간 활동 인식 시스템

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Abnormal Human Activity Recognition System Based on CNN For Elderly Home Care

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ABSTRACT

Changes in a person's health affect one's lifestyle and work activities. According to the World Health Organization (WHO), abnormal activity is growing faster in people aged 60 or more than any other age group in almost every country. This trend steadily continues and expected to increase further in the near future. Abnormal activity put these people at high risk of expected incidents since most of these people live alone. Human abnormal activity analysis is a challenging, useful and interesting problem among the researchers and its particularly crucial task in life and health care areas. In this paper, we discuss the problem of abnormal activities of old people lives alone at home. We propose Convolutional Neural Network (CNN) based model to detect the abnormal behaviors of elderlies by utilizing six simulated action data from daily life actions.
Keyword: Smart homes, Convolutional Neural Networks, Abnormal behavior detection

1. INTRODUCTION

Recent studies show that the proportion of the elderly in the most of countries in the world is increasing. So, a major part of these people has health problems that need long-term care, including nursing at home or frequent hospitalization. Hospitalization and nursing care for 24 hours is not possible due to the high cost and limited recourses in hospitals. The detection of early signs of motion and cognitive impairment (MCI) via activity recognition will be helpful to track motion and cognitive skills of the elderly, Therefore, the government is interested in using technologies to support independent living and healthcare for the elderly population. The advancement of technology in recent years led to the development of cheap video sensors which can be used in face recognition systems for elderly care at a safe and smart home. the aim of This research is explaining a health care system for elderly people to recognize abnormal activities that detect, automatically, unusual behavior and raises an alarm. Unfortunately, there is no dataset on abnormal behavior of elderly people and Producing such a dataset needs time and adequate experimental environment. In this situation, data simulation can be a solution [1]. Therefore, in this paper, we used six simulated data of abnormal activity from the daily life actions of elderly people that need emergency medical help; headache, vomit, faint, chest pain, forward fall, and backward fall [2].

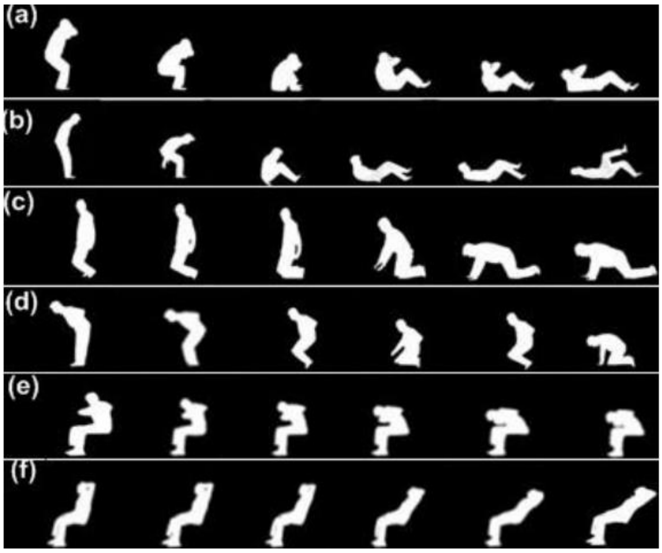
2. RELATED WORK

In recent years, more focus is on the recognition of human activities in daily life activities (ADL). But today, recognizing the activities of the elderly at home is one of the areas that has attracted many researchers. Activity recognition can be typically viewed as a classification problem where many machine learning techniques can be applied such as SVM [3] Naïve Bayes methods [4], Restricted Boltzmann Machines (RBMs) and Markov Logic Networks, Hidden Markov Models (HMMs).

3. METHODOLOGY

To use CNNs in abnormal behavior detection tasks, the following steps are proposed: Firstly, a dataset includes six activity from the daily life actions has been modified in order to simulate abnormal behaviors related to elderly people.

Secondly, this dataset is segmented into time-slices by using a sliding window method as described in [5]. Thirdly, raw data is mapped into last-fired representations as described in [5]. Fourthly, CNNs are trained to recognize abnormal activities. Lastly, tested the trained model by another dataset (Aruba dataset) that consists of daily life activities at home In Fig 1, the simulation dataset for six abnormal activities are described.



(Fig. 1.) Six simulated data of abnormal activity (a) faint (b) backward fall (c) forward fall (d) vomit (e) chest pain, and (f) headache.

3.1. Convolutional Neural Networks (CNNs)

A Convolutional Neural Network (CNN) is comprised of one or more convolutional layers and then followed by one or more fully connected layers as in a standard multilayer neural network. A CNN consists of a number of convolutional and subsampling layers optionally followed by fully connected layers. The input to a convolutional layer is a m × m × r image where m is the height and width of the image and r is the number of channels. In our study, r is 1 since time-slice input matrices have only one channel.

The convolutional layer will have k filters (or kernels). A local filter with a size of n × m × q is used to extract useful feature patterns on the given input. Here, n is the height of the filter, m is the width of the filter and q is the number of filters used. The size of the filters gives rise to the locally connected structure which is each convolved with the image to produce k feature maps. At first, the weight of these filters is initialized randomly and then CNN learns these weights on during the training process. In this paper, we used random uniform initialization for initializing the filter and stochastic gradient descent for optimizing the values during the training. Activation function as an additional process was utilized after every convolution operation. In this study, the activation function is RectifiedLinear Unit (ReLU). Then a max-pooling layer is added to the network. The fully connected layer used is a traditional Multi-Layer Perceptron. The goal of this layer is to use these features for classifying the input image into various classes based on the training dataset. CNNs can contain one or more pairs of convolutional and max-pooling layers and the top layers in CNNs are stacked by one or more fully connected normal neural networks. In the training stage, CNN parameters are estimated by standard forward and backward propagation algorithms to minimize an objective function.

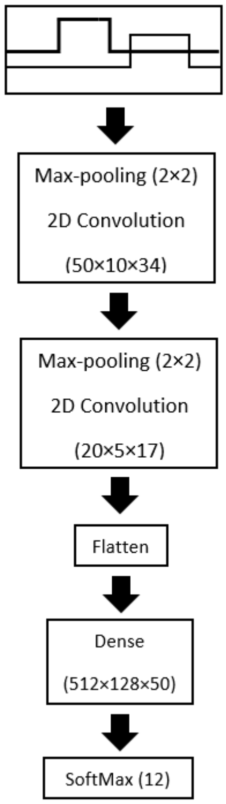
3.1.1 abnormal Activity detection

For recognizing abnormal behaver, training data of the dataset and their Relating labels are trained into CNNs. The model assigns a class label to each data with a confidence value. At first, the mean of confidence values of training data for each class is calculated as follows:

$$m_j = \frac{1}{N}\sum_{t=1}^{N} p_t \qquad (1)$$

where m_j is the mean confidence value of class j and p_t is the confidence value for training data of that class and N is the total number of data in that class.

2D Convolution Neural Network is the method that we used. In this model, convolution is done on both dimensions. 100 filters with a size of 10 × 34 are used in the first convolutional layer which is followed by a 2 × 2 max-pooling. Then another 2D convolution operator is added this time with 20 filters with the size of 5 × 34. In Fig 2, The method architecture is shown.



(Fig. 2.) Convolutional Neural Network architectures used

4. RESULTS

To investigate the activity recognition success, the following metrics are used: Recall and Accuracy.

$$\text{Recall} = \frac{1}{N}\sum_{t=1}^{N}\frac{TP_i}{TT_i} \quad (2)$$

$$\text{Accuracy} = \frac{\sum_{i=1}^{N} TP_i}{\text{Total}} \quad (3)$$

Here, TP is true positive, TT is total number of data, N is the number of classes in a specific class of the dataset and Total is the total number of data of all classes in the dataset. We trained Six simulated data of abnormal activity by CNN with 2D convolution and lastly used Aruba dataset for testing our proposed system. These results indicate that this system has the capability of detecting abnormal elderly activities and it can be used in the smart home if we can improve the simulated dataset. The result is shown in Table 1.

Table 1 Activity recognition results with CNN-2D on Aruba dataset

	CNN-2D
Recall	39.75%
Accuracy	78.37%

5. CONCLUSIONS

The paper presented a system based on CNN for recognizing abnormal behavior that uses for elderly home care. this system trained by the simulated dataset consisting of six abnormal activities; headache, vomit, faint, chest pain, forward fall, and backward fall. The goal of this research is to improve the quality of elderly's life by recognizing abnormal activities from their daily life to help them live as independently. Firstly, we used the simulated dataset for training CNN to recognize six abnormal behavior in the elderly daily life. Lastly tested the trained model by another dataset that consists of daily life activities at home. This system can detect the abnormal activities and it is able to care elderly at home but some problems are observed during system implementation that limits accuracy. one problem is the size of the simulated dataset is small and that did not support all the behavior and another one is the similarities in postures of different activities. Future works can focus on these problems.

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