Human Gait Abnormality Detection using Low Cost Sensor Technology

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Abstract. Detection of gait abnormality is becoming a growing concern in different neurological and musculoskeletal patients group including geriatric population. This paper addresses a method of detecting abnormal gait pattern using deep learning algorithms on depth Images. A low cost Microsoft Kinect v2 sensor is used for capturing the depth images of different subject's gait sequences. A histogram-based technique is applied on depth images to identify the range of depth values for the subject. This method generates segmented depth images and subsequently median filter is used on them to reduce unwanted information. Multiple 2D convolutional neural network (CNN) models are trained on segmented images for pathological gait detection. But these CNN models are only restricted to spatial features. Therefore, we consider 3D-CNN model to include both spatial and temporal features by stacking all the images from a single gait cycle. A statistical technique based on autocorrelation is applied on entire gait sequences for finding the gait period. We achieve a significant detection accuracy of 95% using 3D-CNN model. Performance evaluation of the proposed model is evaluated through standard statistical metrics.

Keywords: Gait abnormality · Microsoft kinect sensor · Depth image · Convolutional neural network · Pathological gait.

1 Introduction

In today's world biometrics has been integrated in every possible aspects starting from clinical application to security systems. Human gait has been appeared to be a significant sign of health condition. Gait investigation is thus useful to acquire important information regarding the growth of different neurological diseases such as Parkinson's [1] or diabetes [2]. By tracking and analyzing these gait information, an early interpretation of sicknesses can be detected which can assist patients with finding the best possible solution.

There are mainly two approaches for analyzing the gait patterns: wearable sensors [7, 6] and non-wearable sensors [8]. Non-wearable sensor-based techniques can be further divided into two categories: marker-based and marker-less approaches. The advantage of using marker-less approach is that there is no necessity of direct body contact with the subject thus it can be acquired at farther distance [3]. Among the marker-less approaches microsoft kinect sensor has attracted many researchers in gait analysis because of it's cost effectiveness and minimal setup requirement [4]. Utilization of kinect depth image sequence is better to create appearance-based gait model. It can incorporate more information than the basic grayscale-based methods [5].

The aim of this research is to create a model for pathological gait detection through understanding depth images of subject's gait sequences. These images are captured using single kinect sensor placed perpendicular to subject's left side. Subjects are asked to simulate the equinus gait pattern for collecting abnormal gait patterns. One of the potential utilities of the method is automatic feature learning and this system can be used for finding patients with equinus deformity. It's a very common feature of cerebral palsy patients so it will be beneficial to decide abnormality. The importance of using our method is that existing method used by the clinician is highly subjective and prone to error whereas our method quantitatively assesses gait dynamics and produce more reliable results. It is also a cost effective device for gait abnormality detection. We propose an algorithm for image segmentation. It can be divided in three steps. In the first step we calculate all the second order maximums. These maximums are the peak of the mounds in the histogram where every mound represent an object. A slice is created around the mound to find the depth range of the object. This slice is converted into mask for the image and after this median filtering is done. At the end we calculated the range of x and y values for the person and a rectangular box is created with this range to extract the person. This process generates a unique segmentation of an object. The robust 3D-CNN architecture is applied for detection of abnormal gait patterns.

The analysis of related works are described in section 2. The data collection process is explained in section 3. Section 4 represents the image segmentation algorithm and classification model. The experimental results and discussions are described in section 5. This work is concluded by providing a possible future work direction in section 6.

2 Related Work

Many researchers applied machine learning algorithms such as logistic regression [11], support vector machine (SVM) [12], hidden markov model (HMM) [10] and clustering [9] to detect abnormal gait patterns with kinect skeletal data. These methods were related to model-based approach for human gait analysis. Whereas model-free approaches focused on silhouettes shapes or the complete motion of human bodies [13]. The advantage of model-free approaches was lower computational costs as compared to model-based approaches which motivates us to carry out this research in this direction.

A method of behavioural abnormality detection was proposed by [14] through extracting the activity silhouette of the subjects. It was further compared with a base model which was constructed by analyzing gait patterns of multiple persons. RGB images were used for detecting abnormal patterns [15]. Those depth images were applied on many gait related applications but none of the researchers used them directly for abnormality detection yet. The depth video-based gait recognition was done using Deep learning methods such as CNN method after extraction of local directional pattern features from the depth silhouette images [16]. A novel approach was proposed by [17] for human identification in depth images using histogram analysis.

Kinect (v2) offers five different data streams [19] out of which skeletal data stream are used extensively in clinical purposes [20, 21] for its simplicity to track joint positions directly. Vipani et al. [22] also used logistic regression for classification of healthy and pathological subjects. Kozlowska et al. [23] used MARS model to investigate the trends in spatial and temporal gait parameters during treadmill walking. This concept has been used by S. Chakraborty et al. [24] in analysing non-linear data, to detect gait pathology.

3 Data Collection Procedure

A single kinect sensor is placed perpendicular to subject's left side. The position of kinect is 180 cm horizontally from the treadmill and 94cm vertically from ground. Ten physically fit young subjects (age (years): 24.3 ± 2.45 and height (cm): 163.29 ± 8.72 , sex: 4 male & 6 female) are chosen for data acquisition. For abnormal gait detection subjects are asked to simulate the Equinus gait patterns. It is a very common foot deformity in cerebral palsy patients. Equinus gait pattern can be explained by ankle plantar flexion throughout the complete gait cycle. The videos are captured at 3 km/h treadmill speed for 50 sec time period. This dataset has a total of 4k depth images of size $311 \times 161 \times 3$ which is an image with 3 channels and it's 2D projection with 60:40 normal and abnormal gait ratio. We are using gray-scale depth images so the pixel intensity varies from 0-255. By using histogram analysis, we are only analysing the frequency of this 256 intensity levels. The segmented images of 60% subjects are taken as training set, 20% for validation set and rest 20% for testing set. We use a system with a NVIDIA's GeForce Titan XP GPU with 12 GB RAM for implementation of deep learning algorithm on gait data.

4 Proposed Method

This section explains the method for pathological gait detection. We collect depth video of different normal and abnormal subjects using single Kinect sensor. The gait sequences are extracted from the videos for further processing. The extracted gait frame, depicted in Fig. 2a contains a lot of unnecessary information. We apply histogram analysis method [17] for detecting region of interest of the image. This technique provides a benefit of analyzing only array of 256 numbers instead of the complete depth image which reduces the computational cost. We use gray-scale depth images so the pixel intensity values from 0-255. By using histogram analysis, we analyze the frequency of this 256 intensity levels. The algorithm 1 describes the procedure for image segmentation.

Algorithm 1 Algorithm for Image Segmentation(IS)

INPUT: $inpimg = Depth\ image\ of\ size\ L \times M \times N$
OUTPUT: $oimg = Segmented\ depth\ image$

procedure IS($inpimg$)
  $hist$ = histogram($inpimg$)
  $hist\_max$ = second_order_maximas($hist$)
  for i = 1:length($hist\_max$) **do**
    $slice[i] = hist\_max[i]$, $t = 0$
    while $(hist[hist\_max[i] - t] > hist[hist\_max[i] - t - 1])$ and $(hist[hist\_max[i] + t] > hist[hist\_max[i] + t + 1])$ **do**
      $slice[i]$.append($[hist\_max[i] - t - 1,\ hist\_max[i] + t + 1]$)
      $t = t + 1$
  $mask = slice[1]$
  for each point p in $inpimg$ **do**
    if p is not in $mask$ **then**
      $p = 0$
  img_filt=median_filter($inpimg$)
  Initialize $sumlist$ as an empty array of length L
  for x = 1:L **do**
    $sumlist[x]$=sum($img\_filt[x, :, 1]$)
  ly_range=first_nonzero($sumlist$)
  uy_range=first_valley($sumlist$)
  Initialize $sumlist$ as an empty array of length M
  for y = 1:M **do**
    $sumlist[y]$=sum($img\_filt[:, y, 1]$)
  lx_range=first_nonzero($sumlist$)
  ux_range=first_valley($sumlist$)
  $oimg$=$img\_filt[lx\_range$:ux_range, ly_range:uy_range, :]
  Return $oimg$

Algorithm 1 is divided into 3 steps. In the first step, we calculate all the second order maximums. These maximums are the peak of the mounds in the histogram where every mound represents an object. A slice is created around the mound to find the depth range of the object. This slice is converted into mask for the image and after this median filtering is done. At the end we calculate the range of x and y values for the person and a rectangular box is created with this range to extract the person. The histogram of the image (Fig. 2a) is shown in Fig. 1a where all the local maximums are marked by outlined circles and all the second order maximums are marked by filled circles. It demonstrates

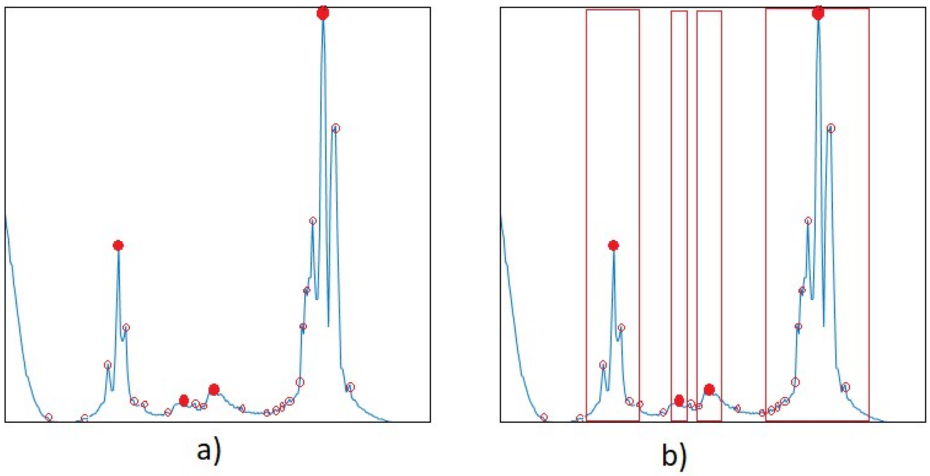

Fig. 1. a) Depth image's histogram. b) Depth image's histogram with slices marked

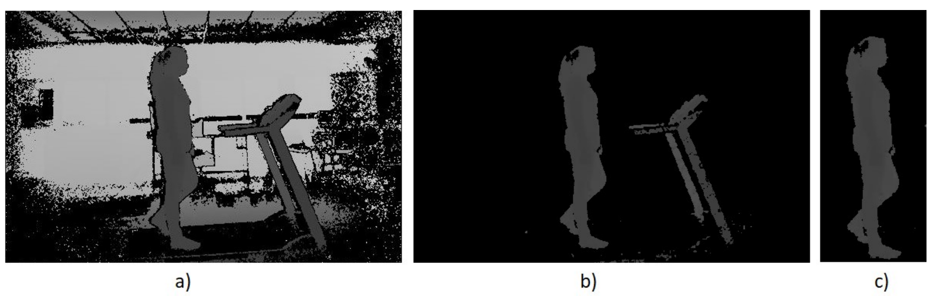

Fig. 2. a) Original depth image. b) Filtered image. c) Segmented image

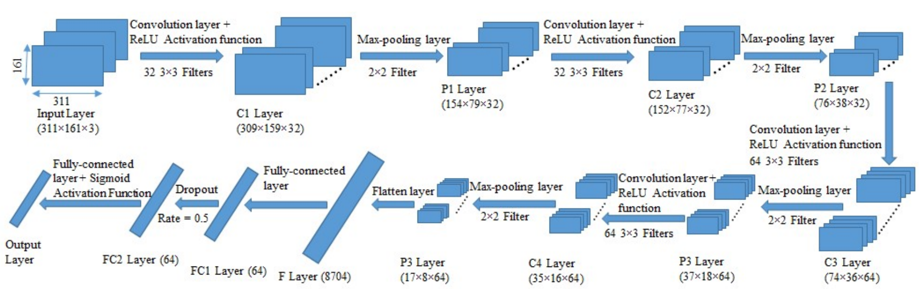

Fig. 3. CNN Architecture

the histogram plot of the image where X axis represents the pixel intensities (0-255) and Y axis represents the frequency of this pixel intensities in the image. Foreground subtraction is done by analyzing the pixel intensities and finding the range of depth values where the person lies. Pixel intensities along Y axis is summed up and plotted to find in which pixel range (in X axis) person lies and same is repeated along X axis so that we obtain all the 4 coordinates of a rectangular box which perfectly fits the person. This range is calculated for all the images in the cycle and their union is taken to cover the complete human motion in the segmented image. The depth image's histogram with marked slices is illustrated in Fig. 1b. We apply median filtering technique to produce better noise-free results (Fig. 2b). Since the subject and treadmill are at same depth so histogram analysis is not able to remove the handrail from the image. Therefore, we analyze the human shape while walking on treadmill through creating an appropriate rectangular box around the subject. The final segmented output image is presented in Fig. 2c.

We apply CNN models for automatic extraction of gait signature and detection for abnormal gait patterns. It is an efficient deep learning technique to process high dimensional data such as images and videos. It has the ability to capture important features without human intervention. The proposed CNN architecture for detecting abnormal gait patterns is illustrated in Fig. 3. This architecture has four 2D convolution and four max-pooling layers with ReLU activation function. This activation function is used for adding the non-linearity in the model. A sigmoid activation function is also used at the last layer for classification. The drawback of this 2D-CNN model includes inability to establish relationship between consecutive frames. Therefore, this model only deals with the spatial features. Since the gait signal carries spatio-temporal information so it is required to consider both the features. To capture the temporal information of gait signal we create stacked cycles by stacking all the images from a single gait cycle and train them with 3D-CNN model.

In order to find a single gait cycle, we apply autocorrelation technique on entire gait sequences [18]. It computes correlation coefficients between the first frame and all the subsequent frames. The number of frames in between two successive peaks is taken as gait period. For our dataset the resulting gait period is 20 frames/cycle. After creating stacked cycles, we use a 3D-CNN architecture for classification of abnormal gait patterns. The architecture of this model has the same set of layers and number of filters as shown in Fig. 3. The only few differences are instead of 2D convolution, 3D convolution is used and the convolution and pooling layer filers are changed to $(3 \times 3 \times 1)$ and $(2 \times 2 \times 1)$ respectively. In CNN architecture Fig. 3 the size of the depth image is $(311{\times}161{\times}3)$ in input layer.

5 Result Analysis & Discussion

The objective of this work is to detect the abnormal gait patterns using low cost Kinect device. Depth videos are captured using single kinect sensor. The image segmentation algorithm is applied to generate foreground subject. These foreground images given as input to CNN model. Multiple CNN models are implemented with varying number of layers and filters to obtain the optimal CNN model. The detection accuracies of these models are given in Table 1. We obtain the best result (94.3%) for the CNN model having 4 convolution layers and (32, 32, 64, 64) number of filters. The detail architecture of this model is presented in Fig. 3. We use 60% of the dataset for training set and the remaining 40% is equally divided into validation and testing dataset. The model accuracy and loss for training and validation dataset are shown in Fig. 4 and Fig. 5 respectively. The loss functions for this work is considered as binary cross-entropy.

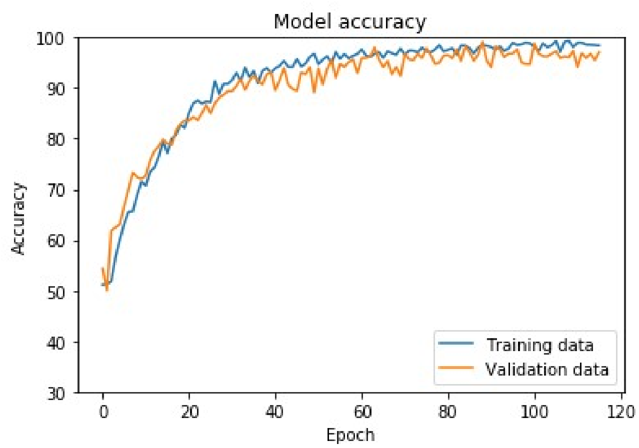

Fig. 4. Training and validation accuracy per epoch for 2D-CNN model

It is observed from this experiment that 2D-CNN is not capable of extracting temporal features. Therefore, we combine all the frames collected from single gait cycle and trained a 3D-CNN model on them to extract temporal features. After training this model is used for detecting abnormal gait and it produces 95% detection accuracy which is slightly higher than the accuracy achieved by 2D-CNN. The model accuracy and loss per epoch for training and validation dataset are shown in Fig. 6 and Fig. 7 respectively. It is clearly visible from these graph that 2D-CNN takes around 120 epoch for convergence whereas 3D-CNN takes 60 epoch. It infers from this analysis that 3D-CNN takes less amount of training time to produce the result. The validation loss for 2D-CNN model (Fig. 5) is not properly converged which infers that 3D-CNN model is computationally more efficient than 2D-CNN model.

The performance evaluation of these models are measured using standard statistical metrics, precision, recall, F1 score and detection accuracy which is depicted in Table 2. It is observed that the 3D-CNN model outperforms the 2D-

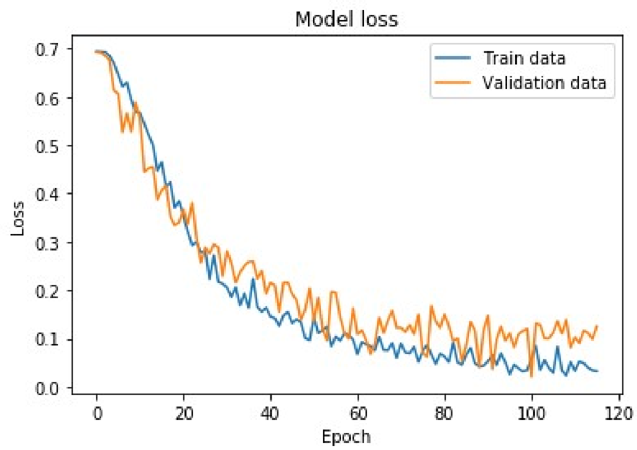

Fig. 5. Training and validation loss per epoch for 2D-CNN model

Table 1. Detection accuracy by varying no. of convolution layers and filters

No. of Conv Layers	No. of filters	Testing Accuracy (%)
2	(32, 64)	89
3	(32, 32, 64)	92.6
3	(32, 64, 64)	93.6
4	(32, 32, 64, 64)	94.3
5	(16, 32, 32, 64, 64)	94.1

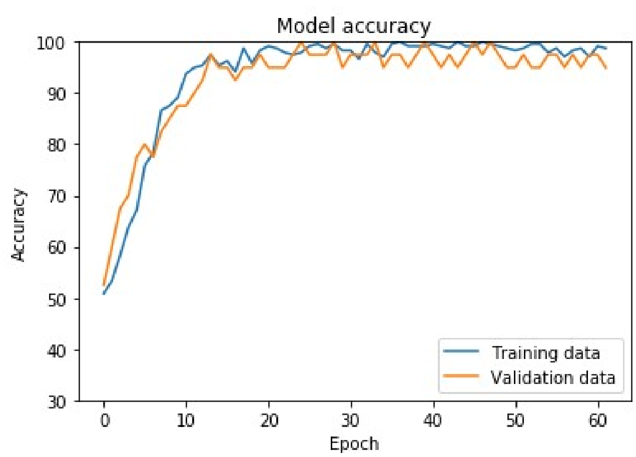

Fig. 6. Training and validation accuracy per epoch for 3D-CNN model

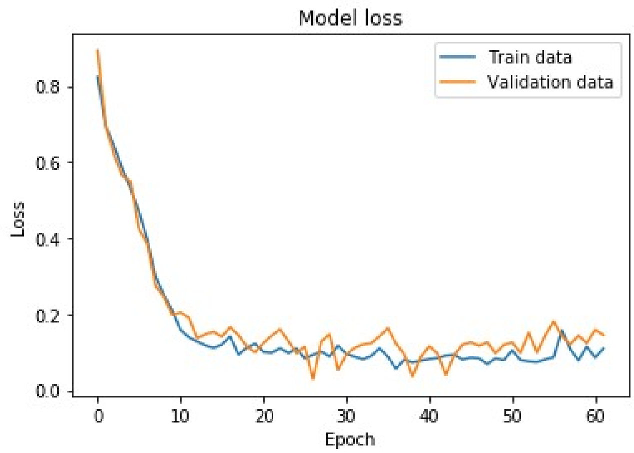

Fig. 7. Training and validation loss per epoch for 3D-CNN model

CNN model. We also examine model performance through receiver operating characteristic (ROC) curve which is illustrated in Fig. 8. The area under the ROC curve for 3D-CNN is 95% which clearly demonstrates it's efficiency for detection of abnormal gait patterns.

Table 2. Performance evaluation metric for CNN models

Model	Testing Accuracy(%)	Precision	Recall	F1 Score
2D-CNN	94.3	0.986	0.907	0.944
3D-CNN	95	1.00	0.909	0.952

6 Conclusion & Future Work

Microsoft kinect v2 sensor along with deep learning techniques are used for detection of pathological human gait patterns. The equinus foot deformity has been simulated by the subjects. In this work the 3D-CNN model has been found to be more suitable in comparison to 2D-CNN model. The detection accuracy achieved by 3D-CNN model is 95% which is better than the 2D-CNN model. The future work can be extended to include actual abnormal gait data and different types of pathological patients for detection of clinical gait abnormality. We also plan to apply k-fold cross validation method to demonstrate the robustness of our proposed model and compare with state-of-the-art methods.

Currently, the aim of the research is identifying abnormal gait patterns using low cost sensing technology to measure the efficiency of Microsoft Kinect device

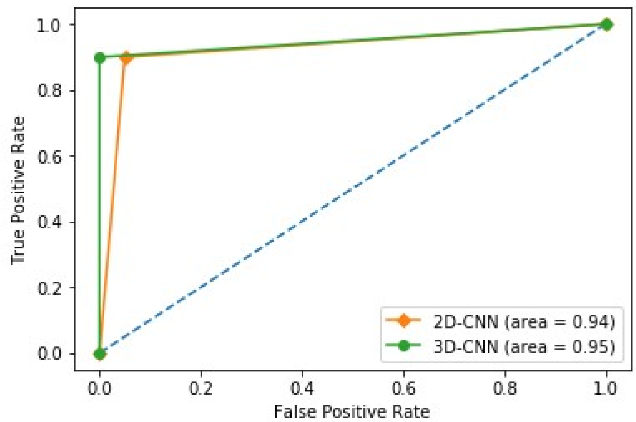

Fig. 8. ROC curve for CNN models

for clinical gait analysis. The comparison with other models is planned in future research work.

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