

Cerebral Infarction Rehabilitation Evaluation with Posture Analyses

Author: Yutian (Tim) Fan

School: Milton Academy

State: Massachusetts, USA

Supervisor: Jundi Wang



Title:

Cerebral Infarction Rehabilitation Evaluation with Posture Analyses

Project researcher and author:

Yutian (Tim) Fan

Abstract:

A cerebral infarction is a brain illness caused by a blockage in or narrowing of the arteries that supply blood and oxygen to the brain. The restricted amount of oxygen to the brain results in varying levels of disorder in the limb function of patients, severely affecting their normal lives. For cerebral infarction patients, physical rehabilitation is crucial in the early stage of their illness. The correct instruction of rehabilitation exercises can effectively restore the patient's limb function, reduce the chance of reoccurrence and improve the patient's daily life.

In order to provide cerebral infarction patients effective early treatment, this project strives to develop a motion evaluation model based on deep learning. In order to enhance the instruction of rehabilitation exercises, the project's model defines 6 standard exercises as training input. It then employs the python Openpose framework to extract the coordinates of 18 joints of the human body, and traces the trajectory of these 18 joints when a person carries out one of the standard exercises. The trajectory of the joints during the exercise is used to train the LSTM network. The final model can be used as a guiding model for rehabilitation training.

Keywords:

Posture Analyses, Cerebral, LSTM

Contents

1. Introduction

- 1.1 The inspiration of this project
- 1.2 Current rehabilitation practices
- 1.3 Experiment design
- 1.4 Expectation for the future

2. Research

3. Tasks of the Posture Analyses

- 3.1 Making the data set
- 3.2 Key point extraction algorithm
- 3.3 Building a neural networksa
- 3.4 Data analysis

4. Results

- 4.1 The creation of the data set
- 4.2 The extraction for the standard exercise
- 4.3 The development of an identification system

5. Results display

6. Conclusion

References

Acknowledgements

1. Introduction

This project aims to combine rehabilitation evaluation with deep learning, which not only reduces the workload of necessary medical staff, but also makes the costly rehabilitation available to those who could not formerly afford it.

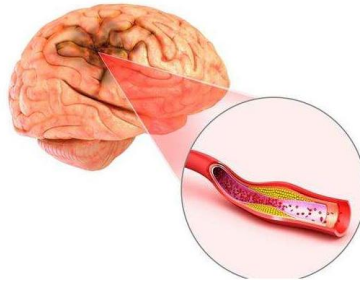


Figure 1: Head vascular blockage

1.1 The inspiration of this project

I first considered this project during a conversation with one of my friends. We were discussing the fragility of human lives, and he told me how his grandfather passed away due to ineffective rehabilitation after suffering from cerebral infarction. I instantly dove into research. Apparently, even after treatment, some patients are still left with distorted facial expressions and varying degrees of disordered function in speech and limb movements, which affects the lives of patients and their families. I consulted some doctors in my hometown about the rehabilitation practices for patients with cerebrovascular disease, according to the doctors' instructions, I designed six physical rehabilitation exercises. I hope that the techniques of deep learning that I develop will be applied to the rehabilitation of patients to improve their recovery.

1.2 Current Rehabilitation Practices

In order to be a good rehabilitation therapist, one needs to have not only systematic knowledge of rehabilitation, but also maturity and social skills. The number of patients with cerebral infarction in China increased as the population skyrocketed in recent years. To individually evaluate each and every patient is a heavy workload and perhaps even an impossible task. The patients need go to the hospital in order to obtain a professional evaluation, regardless of the severity of their potential

movement disorders. It is incredibly inconvenient for the patients and their family members to make such trips.



Figure 2: Cerebral infarction

1.3 Experiment design

Four volunteers were invited to record the exercises for this project. Each person was recorded doing each exercise 5 times, for a total of 120 videos. I then used the posture analysis algorithm to extract the information and motion trajectory of each joint point in each video. The information were then saved in .json files. In the end, the deep learning network was trained with the data 1000 times to produce a reliable evaluation model.

1.4 Expectation

I expect to create a cerebral infarction rehabilitation evaluation system that uses cameras and computers to capture the patient's limb motion trajectory in real time, extract the position of the joint points accurately, and run that information through the deep learning training model for efficient identification and scoring. Also, I expect to create an app interface and make the program easier to use by common patients who will help the program to get real patients' feedback.

2. Research

Recently, an increasing amount of studies on gait tracking and evaluation in the field of rehabilitation have been published. Hu Z L, Hartfiel A, Tung J, et al. installed Kinect on the walkers to extract leg information for medical posture analysis. Penny J S, David J B, Steven B, et al. used special equipment to differentiate the background from the lower limb and analyze captured posture value. Guo gang Zhu and Lin Cao

uses the Kinect depth sensor to obtain the motion data of the limb, constructs the human skeleton topology according to the change of coordinate of the limb motion, and performs training and motion identification through multiple types of support vector machines.

The characteristics of the human body's movements are diverse and complicated. Some rehabilitation exercises have larger amounts of deviation in joint movements during different stages of exercise, compared to other exercises. The fact that the existing methods do not fully consider this factor during the gait evaluation also causes a certain degree of deviation in the results. At the same time, because Kinect equipment is quite expensive, it cannot be widely used.

3. Tasks of the Posture Analyses

3.1 Making the data set

Based on the doctors' suggestions, this project defines six standard exercises: Stationary walking, lifting the left arm, lifting the right arm, lifting both arms, lifting the right leg, and lifting the left leg. The details of the exercises are as follows:

Exercise	Instruction
Stationary walking	Keep the torso straight, and perform the "high knees" exercise, but slowly. Pay attention to the angle of the torso to the knee.
Lifting the left arm	Keep the torso straight, relax the right arm, and slowly lift the left arm to shoulder-height.
Lifting the right arm	Keep the torso straight, relax the left arm, and slowly lift the right arm to shoulder-height.
Lifting both arms	Keep the torso straight, and slowly lift both arms up and forward to shoulder-height. Then extend the arms sideways and upward till both arms are 45 degrees to the torso.
Lifting the left leg	Keep the torso straight, and lift the left leg until it is 30 cm above the ground.

Lifting the right leg	Keep the torso straight, and lift the right leg until it is 30 cm above the ground.
-----------------------	---

3.2 Key Point Extraction Algorithm

Due to the flaws of more traditional methods, this project uses the neural network-based human pose identification method, Openpose. The core of Openpose is Part Affinity Fields, a bottom-up human pose estimation algorithm. First, Openpose identifies the position of the key points of the human body, and then obtains the thermal map of each key point through a large amount of data. Second, Openpose discovers and statistically analyzes the Gaussian distribution each joint point, which provides the position of the joint point of the body with the Gauss Score trained by the neural network. Finally, the points are connected to obtain the overall patterns of the person's body. This method works well in multi-tasks identification.

The process of this analysis is demonstrated in Figure 3. The input is $W \times H$ image. Both the confidence map set S of the body position and the part affinities set L , which represents the connection between points, could be obtained by a trained model. Analyzing the two sets provides the 2D image of all the points on all the human bodies that can be detected in the original frame. This method creatively uses the deep learning neural system and identifies the joint points on both human bodies.

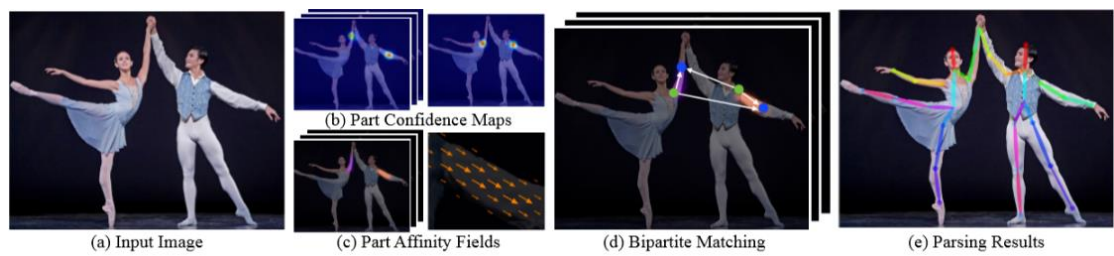


Figure 3 Process of identifying human body joints points

3.3 Building a neural networksa

This project uses Long Short Term Memory Neural Network (LSTM). It was developed by Hochreiter and his colleagues as a deep learning network based on chronological order. A group of researchers, including Gers, added Forget Gate based on the research of Hochreiter. This project used the most basic LSTM model, which

includes 34 hidden layers. The main calculations of the LSTM model useful for this project are:

$$i_t = \sigma(W_i * (h_{t-1} + x_t) + b_i) \dots \dots \dots \text{formula (1)}$$

$$f_t = \sigma(W_f * (h_{t-1} + x_t) + b_f) \dots \dots \dots \text{formula (2)}$$

$$o_t = \sigma(W_o * (h_{t-1} + x_t) + b_o) \dots \dots \dots \text{formula (3)}$$

$$\tilde{C}_t = \tanh(W_c * (h_{t-1} + x_t) + b_c) \dots \dots \dots \text{formula (4)}$$

$$C_t = f_t * \tilde{C}_t + i_t * \tilde{C}_t \dots \dots \dots \text{formula (5)}$$

$$h_t = o_t * \tanh(C_t) \dots \dots \dots \text{formula (6)}$$

Formulas (1)-(3) are the formulas for Input Gate, Forget Gate, and Output Gate, respectively. Formulas (4) and (5) update the plot of points. Formula (6) calculates the final output of the memory units. The LSTM model comprises formulae based on learner data set analyses. LSTM network has good stability. It is suitable for word recognition and LSTM network can avoid the disappearance of the weight due to the depth of the neural network.

The LSTM structure is as follows:

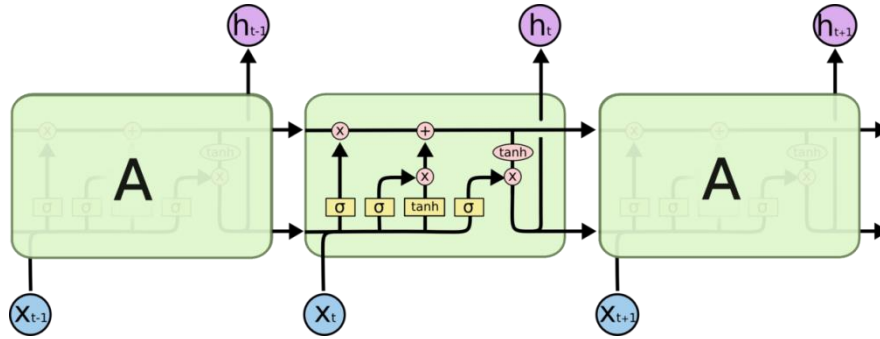


Figure 4:LSTM Structure

3.4 Data Analysis

The input of LSTM is the image located in the frame sequence with the serial number n_steps . The image is chronological. The output is the 2D location of the 18 body joint points, with each of their category tags. The tags are the names of the 6 standard rehabilitation exercises: stationary walking, lifting the left arm, lifting the right arm, lifting both arms, lifting the left leg and lifting the right leg.

The input of a single frame (j stand for joint) is saved as:


```
[j0_x , j0_y , j1_x , j1_y , j2_x , j2_y , j3_x , j3_y , j4_x , j4_y , j5_x , j5_y , j6_x ,
j6_y , j7_x , j7_y , j8_x , j8_y , j9_x , j9_y , j10_x , j10_y , j11_x , j11_y , j12_x ,
j12_y , j13_x , j13_y , j14_x , j14_y , j15_x , j15_y , j16_x , j16_y , j17_x , j17_y]
```

This project has done a few preprocesses with the data set. The main steps are:

(1) Use Openpose to extract the overall location information of all the joints points of all six rehabilitation exercises. For each patient's body, the position of the x and y values of all 18 joint points in each frame are stored as .json files.

(2) Transform the .json file to a .txt file, keeping only the x and y values in each frame. The purpose of this step is to record the x and y values, their chronology, and the number code, which was created based on each category, and the 2D position data base of the corresponding joint point.

(3) Separate the .txt files to the training set and testing set in the ratio of 4:1. For the same data set, separate the videos into sets of 30 frames, and set the repeat rate as 80%, which means 24 out of the 30 frames repeat. This could speed up the process of training the neural network. During the training, if any joint point is not identified in an image, its location is defined at [0.0,0.0].

4. Results

4.1 The creation of the data set

The project employs six standard exercises, around 2000 frames of each exercise, as shown in Figure 5:



Figure 5 Key point information in json format

4.2 The extraction for the standard exercise

By using the Openpose algorithm, this project divided a video into frames. I recorded the joint points in each frame, saved the information of the location of the joint points, and created training and testing data based on that information, as shown in Figure 6:

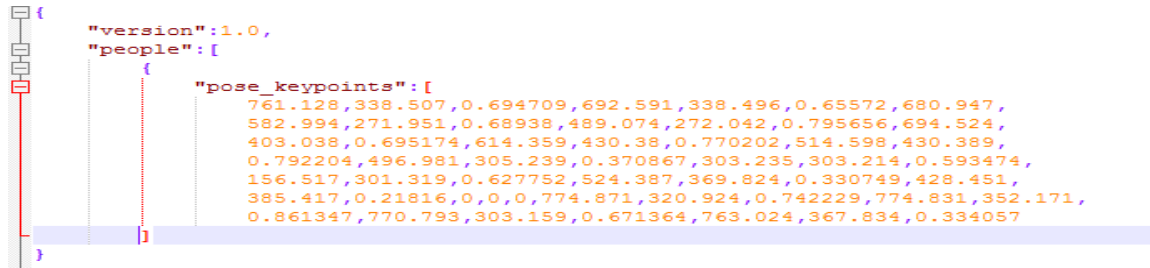


Figure 6 Volunteers show the key points of walking

4.3 The development of an identification system

The system is based on the LSTM training model, trained with the standard exercise inputs 100,000 times. The final model file includes the neural network and network parameters. This project used model files to develop the identification system. After inputting the video of the patient's movements, the project can quickly identify the category of the exercise and evaluate the patient. The main code is:

```
import glob, os
import numpy as np
test_file_X = "X_test.txt"
test_file_Y = "Y_test.txt"
train_file_X = "X_train.txt"
train_file_Y = "Y_train.txt"
data_path = 'H:/mengfu/康复识别/merge_txt/'
activity_list = ['Hands_up', 'Lift_left_arm', 'Lift_left_leg',
'Lift_right_arm', 'Lift_right_leg', 'Walking_still']
num_steps = 25
test_train_split = 0.8
split = False
overlap = 0.85
```

5. Results display

After 1000 times of training, the accuracy of the training set of the model maintained around 98%, after the test on the test set, the accuracy of the identification

of each posture in this experiment is explained by the following paragraphs.

According to the experiment, the accuracy of test sets of the exercises, stationary walking and lifting left leg and lifting right leg, is above 95%, which is a favorable result. The accuracy of test sets of the exercises, lifting both hands, lifting left arm and right arm is below 95%. The results of the identification of these three results has space for improvements. One of the reasons of this unfavorable result might be the similarity of the three exercises. The similarity could affect the accuracy of the tests. Another reason is the inadequate of the training samples.

The changes of the accuracy, loss function, weights and bias in this project are recorded. The changes are visualized with Tensorboard. Figure 7 (a) (b) demonstrate the change of accuracy throughout the 1000 trainings of the network. Figure 8 (a) (b) demonstrate the change of accuracy of loss functions, figure 9 (a) (b) for the weights and figure 10 (a) (b) for the biases.

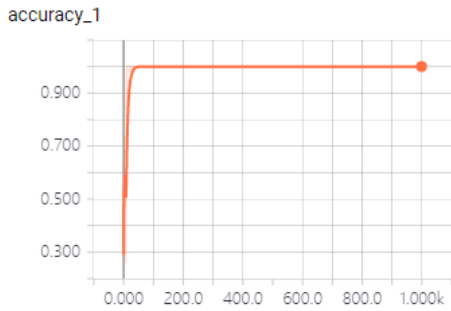


Figure7a Accuracy of training

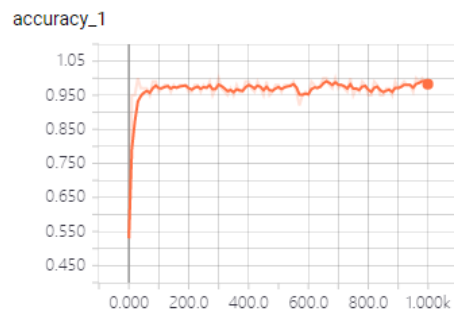


Figure7b Accuracy of test

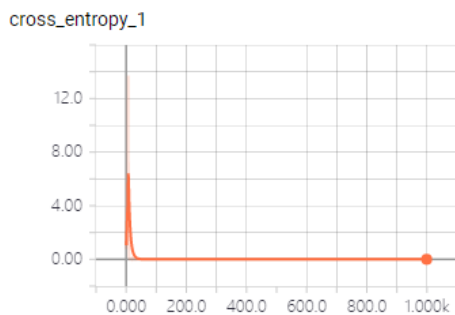


Figure8a Training Loss Function

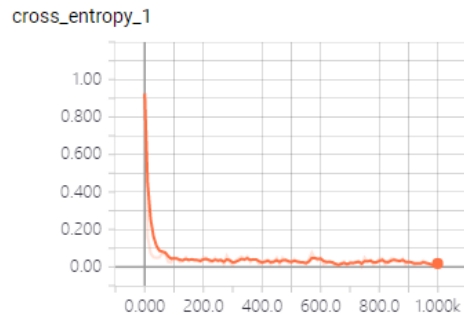


Figure8b Test Loss Function

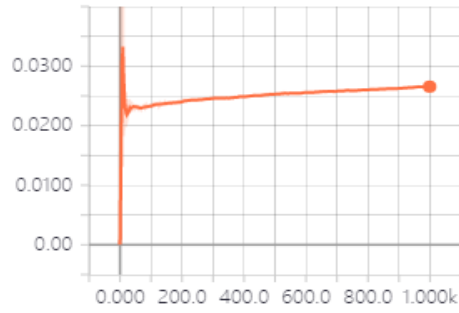


Figure9a Training set weights

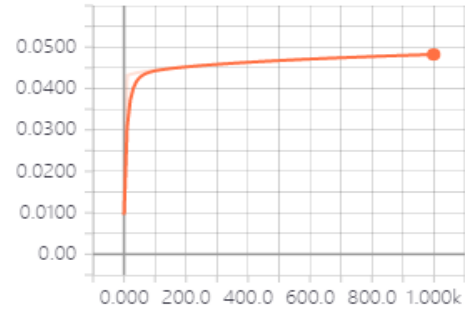


Figure9b Test set weights

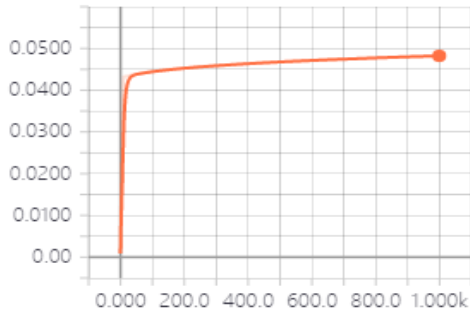


Figure10a Training set bias

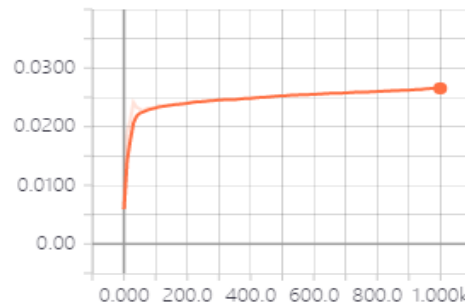


Figure10b Test set bias

Based on the training, the accuracy of the test set reached 95% around the 200th trial, after which, the accuracy still grew slowly. After around 1000 training, the accuracy of the training set is approaching 100%, the accuracy of the test set is around 96.5%. The accuracy of the lost function was a bit unstable only in the first 100 trainings. The accuracy of weight and bias varied in the first 200 trainings, after which the accuracy grew more stable.

6. Conclusion

Based on the data of the experiment, after 10,000 generation of training, the recognition rate of the system on the training set achieved 90%, and 80% on testing set. Both have met the expectation. Identifying lifting right leg and lifting left leg were especially accurate.

This project developed a Cerebral Infarction Rehabilitation Evaluation with Posture Analyses. This system is cheap, convenient and easy to use. This system also does not limit its user with device or medical knowledge requirement. The users only have to input the video to use the system and get an evaluation of their exercise.

This system can directly use a human body's joint's information. After training with a large amount of data, this system has high reliability. Since during the

experiment, only 6 exercises were used and trained 30 minutes each, 80% recognition accuracy is pretty decent. However, there are a lot of space for improvement. First, the standard exercises has only a small amount of data. It would be difficult for the deep learning system to be as effective when dealing with large amount of data. Also, the LSTM network used in this project has 34 hidden layers. More layers could be added to increase accuracy. I plan to take some steps forward in the following fields:

- ✧ Add more training data sets and other different kinds of exercises.
- ✧ Improve the neural network and increase accuracy.
- ✧ Adjust the base line of standard exercise so that the same exercise done by different patients could be identified as one.
- ✧ Create an app interface and make the program easier to use by common patients.

References

- [1] Hu Z L, Hartfiel A, Tung J, et al. 3D pose tracking of walkerusers'lower limb with a structured-light camera on a moving plat-form[C].
- [2] L. Chen, H. Wei, and J. Ferryman, "A survey of human motion analysis using depth imagery[J]." Pattern Recognition Letters, 2013, 34(15): 1995-2006.
- [3] Weinland D, Ronfard R, Boyer E. A survey of vision-based methods for action representation, segmentation and recognition[J]. Computer Vision and Image Understanding, 2011, 115(2): 224-241.
- [4] Ramanathan M, Yau W Y, Teoh E K. Human action recognition with video data: research and evaluation challenges[J]. IEEE Transactions on Human-Machine Systems, 2014, 44(5): 650-663.
- [5] Hu Z L, Hartfiel A, Tung J, et al. 3D pose tracking of walkerusers'lower limb with a structured-light camera on a moving plat-form [C] ||2011 IEEE Computer Society Conference on ComputerVision and Pattern Recognition Workshops (CVP RW) , IEEE, 2011: 29 — 36.
- [6] 胡琼, 秦磊, 黄庆明. 基于视觉的人体动作识别综述[J]. 计算机学报, 2013, 36(12):2512-2524.

Acknowledgements

I would like to offer special thanks to the three volunteers, Chao An, Cheng Zhang and Wulong Zhang, for helping to record the videos of the standard actions. In this process, I communicated a lot about the standard of the exercises, so that every person's video could satisfy the training of the network. Also, thanks to the Fablab for providing equipment and a quiet space for experiments and the supervisor Jundi Wang's professional guide.

Independent Copyright Statement

I solemnly declare that this paper is the independent research results of mine under the guidance of my supervisor. As far as I know, this paper does not contain any research results published or written by other individuals or groups except the quoted part. The people who have given me help and their contributions are clearly stated in the text and I have sincerely expressed my thanks to them. I have the independent copyright and interpretation right of this paper. No individuals or groups may print, publish, sell or disseminate it without permission from me. Once discovered, I will pursue its legal responsibility. If there is anything untruth occurs, I will assume all responsibilities.

Project Researcher: Yutian (Tim) Fan Tim Fan

Supervisor: Jundi Wang 王君迪

Date: August 25th, 2019