Automatic Health Problem Detection from Gait Videos Using Deep Neural Networks

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Abstract—Goal: The aim of this study is developing an automatic system for detection of gait-related health problems using Deep Neural Networks (DNNs). Methods: The proposed system takes a video of patients as the input and estimates their 3D body pose using a DNN based method. Our code is publicly available at https://github.com/rmehrizi/multi-view-pose-estimation. The resulting 3D body pose time series are then analyzed in a classifier, which classifies input gait videos into four different groups including Healthy, with Parkinson’s disease, Post Stroke patient, and with orthopedic problems. The proposed system removes the requirement of complex and heavy equipment and large laboratory space, and makes the system practical for home use. Moreover, it does not need domain knowledge for feature engineering since it is capable of extracting semantic and high level features from the input data. Results: The experimental results showed the classification accuracy of 56% to 96% for different groups. Furthermore, only 1 out of 25 healthy subjects were misclassified (False positive), and only 1 out of 70 patients were classified as a healthy subject (False negative). Conclusion: This study presents a starting point toward a powerful tool for automatic classification of gait disorders and can be used as a basis for future applications of Deep Learning in clinical gait analysis. Significance: Since the system uses digital cameras as the only required equipment, it can be employed in domestic environment of patients and elderly people for consistent gait monitoring and early detection of gait alterations.

I. INTRODUCTION

Gait analysis is the systematic study of human walking for recognizing of gait pattern abnormalities, postulating its causes, and proposing suitable treatments. Gait analysis is commonly used in clinical applications for recognition of a health problem or monitoring patient’s recovery status. The traditional clinical gait analysis is performed by clinicians who observe the patients’ gait characteristics while he/she is walking. However, this method is subjective and depends on the experience and judgment of the clinician. As a result, it can lead to a confusion and has a negative effect on the diagnosis and treatment decision making of pathologies [1].

The process of clinical gait analysis can be facilitated through the use of new technologies, which allow an objective measurement and reduces the confusion and error margin of the subjective methods. These new technologies include: optical motion capture systems capable of detecting position of reflective markers placed on the surface of skin; wearable inertia sensors, which measure body motion using a combination of accelerometers and gyroscopes; force plate platforms imbedded on the walkway to report ground reaction forces and torques; and finally Electromyography (EMG) sensors placed on the surface of skin to monitor muscle activities. Despite the accuracy achieved by these state-of-the-art technologies, there are drawbacks that limit their use. For example, cost of the equipment, laboratory setting requirement, and movement obstruction due to the body sensor attachment are most important drawbacks, which make these technologies infeasible to be utilized in patients’ natural living environments for a continuous gait monitoring and limit their use to hospitals and clinics.

In this study, an automatic system for gait analysis with the aim of detecting health problems is developed, which analyzes and classifies gait patterns using digital cameras as the only required equipment and provides a tool for constant and ubiquitous gait monitoring of patients and elderly people while living in their homes. The input videos is converted into 3D joints coordinates (3D body pose) using our proposed DNN based method and the resulting time series of the 3D joints coordinates are analyzed in another DNN for health problem detection. This study targets three health problems including “Parkinson”, “Post Stroke”, “Orthopedic”, and the fourth class is “Healthy”, used as a reference. The contribution of the present study is three-fold:

- We propose an automated system to detect gait-related health problems from videos captured by pervasive digital cameras and implement a thorough experimental study to validate it.
- We develop a DNN based method to estimate 3D body pose directly from videos and validate the results against a marker-based motion capture system.
- We develop a DNN based classifier to detect health problems from estimated 3D body pose.
II. LITERATURE REVIEW

We review related works in two categories. The first category is an overview of the previous methods for video-based human motion capturing with focus on biomechanical application. The second category, is a summary of recent methods for gait-related health problems classification.

A. Video-based Human Motion Capture

Video-based human motion capture has been excessively studied during the past decades and a variety of computer vision and machine learning approaches have been proposed for 3D human motion tracking and pose estimation [2-4]. It has attracted researchers to investigate the applicability of these approaches in biomechanical and clinical applications in order to address problems associated with traditional human motion capture systems including complex equipment requirement, excessive preparation time, movement obstruction, and controlled environment requirement [5, 6]. In particular, Corazza et al. [7] developed a video-based method for joint kinematics assessment during gait. They used eight cameras to capture multi-view images of subjects and converted these image data to a visual hull by applying background subtraction. Then, a predefined 3D body model is fitted to the visual hull using body part segmentation and least-squares optimization. The same idea was taken to develop an underwater video-based motion capture system for the analysis of arm movements during front crawl swimming [8].

Despite the high accuracy of these methods, they critically rely on background subtraction, which requires a controlled environment and lighting conditions. Furthermore, large number of cameras is needed to construct a precise visual hull surface, which is not always practical in home use.

With the emergence and advances of deep learning techniques, approaches that employ DNN have become the standard in the domain vision tasks including face recognition [9, 10], human activity recognition [11, 12], and human motion tracking and pose estimation [13-15]. DNNs consist of several hidden layers between the input and output layers and are capable of modeling complex non-linear relationships by learning high-level and semantic features from the data. While the focus of the recent DNN-based methods for 3D human pose estimation are on single view and challenging setting [4, 16-19], in this study, we develop a DNN based method to estimate 3D body pose from multi-view images, which is a common setup for the biomechanical analysis experiments. Our method does not require complicated image preprocessing e.g. background subtraction, and achieve accurate results by using only two cameras to record the gait videos in the sagittal plane.

B. Gait-related Health Problem Classification

In the context of clinical gait analysis, machine learning methods such as Support Vector machines (SVM), Artificial Neural Networks (ANN), and Logistic Regression found application in recognizing and classifying specific gait patterns into relevant health problems. Previous studies utilized new technologies such as motion capture systems [20], force plate platforms [21, 22], Inertia Measurement Units (IMUs) [23], and a combination of them [24] to collect gait data and define hand-crafted features for recognizing abnormal gait patterns. In particular, Pogorelc et al [20] used marker-based motion capture system to acquire body motion and defined 13 hand crafted features based on knowledge of medical experts. Then, several machine learning algorithms including k-nearest neighbors and SVM were applied for classification of user’s gait into normal, with hemiplegia, with Parkinson’s disease, with pain in the back, and with pain in the leg. Due to the unavailability of test subjects with actual target health problems, some of the data were acquired by healthy subjects who were asked to imitate those abnormal gait conditions. In another study by Shetty et al. [22], raw data was collected by force plates located under subjects’ foot, then various hand-crafted gait features such as stride, swing, and double support intervals were extracted from raw data and SVM was applied to differentiate Parkinson’s disease from other neurological diseases. Additionally, numerous studies have developed computational models of Parkinson’s disease to investigate the effects of Deep Brain Stimulation on gait dysfunction in Parkinson’s diseases [25-27]. These studies demonstrate the feasibility of machine learning approaches for gait-related health problems classification, however; they require feature engineering to extract useful information from input time series data. Feature engineering relies on the experience of clinicians and demands substantial knowledge in normal and pathologic gait. It becomes more challenging when patients are in the early stage of diseases and their walking patterns look similar to normal gait. Furthermore, extracting hand-crafted features from the input time series leads to discarding a large amount of potentially meaningful information that are represented by the whole time series. Therefore, in this study, we propose a DNN method to extract semantic features from the input data time series and perform classification of user’s gait. Our method does not require feature engineering and the whole times series are fed into a network with the capability of learning and extracting all the useful information from them.

III. METHODS AND MATERIALS

A. Data Acquisition

Our dataset includes walking pattern records of 23 patients with Parkinson’s disease, 22 Pose Stroke patients, 25 patients with orthopedic problems, and records from 25 healthy control subjects. Subjects were asked to walk on a treadmill for about one minute with two digital cameras recording their gait pattern and a synchronized motion capture system directly measuring their body movement. Digital cameras were located on both sides of the subjects (sagittal plane) and had 480x640 pixels resolution. 8 Reflective markers were attached to the neck, chest, left/right hips, left/right knees, and left/right ankles, which were traced by a motion capture system with a sampling rate of 100 Hz.
The aim of our proposed system is detecting gait-related health problems from gait videos. Figure 1 shows an overview of the proposed system, which consists of two DNNs. The first DNN ("Pose Estimator") takes videos as the input and estimates corresponding 3D body pose for each frame to construct 24 (3 directions × 8 joints) time series. Each time series represents position of one joint in one of the three directions (x, y, and z). The second DNN ("Classifier") takes estimated time series as the input and classifies it into one of the four pre-defined groups.

1) Pose Estimator Network

3D body pose is estimated from the videos using our proposed DNN based method. Figure 2 illustrates the network architecture. We first estimate 3D body pose in the camera coordinates and for each view separately. Then, the estimated 3D body poses are transferred into global coordinates and fused across views to improve the accuracy of results.

At first step, videos are split into frames (images) and corresponding 2D joint coordinates are estimated using Hourglass Network [13]. Hourglass Network has achieved state-of-the-art performance on large scale human pose datasets for 2D pose estimation and comprises of encoder and decoder. The encoder processes the input image with convolution and pooling layers to generate low resolution feature maps and the decoder processes low resolution feature maps with upsampling and convolution layers to construct the high resolution heatmaps for each joint. Each value in heatmaps represents the probability of observing a specific joint at the corresponding coordinates. We choose the coordinates with highest probability as the estimated 2D joint coordinates. Then, estimated 2D joint coordinates are processed in a series of blocks comprised of fully-connected layers, ReLU activation function [28], batch normalization [29], dropout [30], and Residual connection [31] to estimate 3D joint coordinates (fig. 2). The architecture of the blocks is similar to the work by Martinez et. al. [16] for 3D human pose estimation from monocular images. In the next section, we explain our proposed technique to modify their network design to handle multi-view setup.

2) Multi-view Fusion

The objective for multi-view fusion is to improve the accuracy of estimated 3D body pose. As mentioned earlier, the output of the Pose Estimator network is the 3D joints position in the camera coordinates. Given the location of the cameras (rotation and translation matrix), the estimated 3D joints position can be transferred into the global coordinates as follow:

\[ \mathbf{P}_i^g = R_i^{-1} \mathbf{P}_i + T_i \]

, where \( R_i \) and \( T_i \) are rotation and translation matrix of camera i, respectively. \( \mathbf{P}_i \) and \( \mathbf{P}_i^g \) represent estimated 3D body pose in camera coordinates i and global coordinates, respectively. Let \( x_{i,j}, y_{i,j}, z_{i,j} \) denote x, y and z coordinates of joint j in view i, and \( x_{i,j}^g, y_{i,j}^g, z_{i,j}^g \) denote x, y and z coordinates of joint j in global coordinates calculated from view i, then \( \mathbf{P}_i \) and \( \mathbf{P}_i^g \) are vectors with size 3xJ, where J is total number of joints (8 in this study):

\[
\mathbf{P}_i = [x_{i,1}, y_{i,1}, z_{i,1}, \ldots, x_{i,J}, y_{i,J}, z_{i,J}]
\]

\[
\mathbf{P}_i^g = [x_{i,1}^g, y_{i,1}^g, z_{i,1}^g, \ldots, x_{i,J}^g, y_{i,J}^g, z_{i,J}^g]
\]

The ideal situation is when the estimated 3D body pose in global coordinates are exactly the same for all the views i.e. \( \mathbf{P}_1^g = \mathbf{P}_2^g = \ldots = \mathbf{P}_n^g \), where n is number of cameras. However, due to the error associates with the estimated 3D joints position, it does not usually happen. The most straightforward technique to fuse the views in order to get the final 3D body pose in the global coordinates (\( \mathbf{P}^g = [x_1^g, y_1^g, z_1^g, \ldots, x_J^g, y_J^g, z_J^g] \)) is by taking average of \( \mathbf{P}_i^g \)’s across views. But in this work, we propose weighted average technique, which takes into account the accuracy of the estimated 2D pose. In other words, we calculate \( \mathbf{P}^g \) as follow:

\[
[x_j^g, y_j^g, z_j^g] = 1/n \sum_{i=1}^{n} w_{ij} \times [x_{i,j}^g, y_{i,j}^g, z_{i,j}^g]
\]

\[
\sum_{i=1}^{n} w_{ij} = 1 \quad \text{for } j = 1, \ldots, J
\]

, where \( w_{ij} \) is equal to the confidence probability of estimated joint j in 2D space obtained from the heatmaps of view i. In other words, for each joint, we assign more weights to the view that estimates 2D pose with higher confidence.

3) Classifier Network

Once we have obtained 3D body pose time series, the final stage is classifying those time series to detect a health problem. Instead of heavy data pre-processing and feature engineering, we feed the raw time series directly to the Classifier network and let the network automatically learn complex feature representations. Our network architecture is shown in figure 3 and it is inspired by Wang et. al. [32] work. It consists of fully convolutional blocks, which act as a feature extractor and include convolutional layer followed by a batch...
normalization [29] and a ReLU activation function [28]. The convolution operation is fulfilled by a fully connected layer and ends with a Softmax layer to produce final label.

Due to unequal video sequences, the time series have a different temporal length, but our designed DNN requires a fixed size input. In order to address this problem, we employ “Window Slicing” technique. Let $TS = [ts_1, \ldots, ts_L]$ denote a time series with length $L$, a slice is a snippet of the original time series with a pre-defined length $l (l < L)$ and a randomly selected start ($i$) as follow:

$$S_i = [ts_i, ts_{i+1}, \ldots, ts_{i+l-1}].$$

We repeat slicing for 50 times and convert each time series into 50 subsequences of a fixed length, which might have overlapping. All of the subsequences are classified independently and in order to produce final label along the whole time series, a “Majority Voting” technique is applied. Another advantage of slicing is data augmentation. By performing slicing, we make the data set 50 times bigger, which helps avoiding over-fitting and increasing the generalization capability. The length of the slice is set to 100 frames (two seconds) that approximately covers on gait cycle and is then down-sampled to 20 frames.

4) Implementation Details

The deep learning platform used in this study is Pytorch and training and testing are implemented on a machine with NVIDIA Tesla K40c and 12 GB RAM. The network was trained in a fully-supervised way with L2 loss function and using Adaptive Moment Estimation (Adam) [33] as the optimization method ($\beta_1 = 0.9, \beta_2 = 0.999$). To evaluate the performance of the proposed system, a 5-fold cross validation was carried out, which assigns %80 of data for training and %20 for testing and repeats it five times to have the results on the whole dataset.

We fine-tuned pre-trained Hourglass model [13] on our dataset with learning rate of 0.00025 and mini batch size of 6 for 20,000 iterations. We then trained the pose estimator network from scratch. We propose a two-stage training strategy in which a network with only two blocks is trained first for a single view input with a starting learning rate of 0.001 and exponential decay for 200 epochs. At the second stage, the network with four block (fig. 2) is further trained for the multi-view input with a learning rate of 0.0001 for 5 epochs. Classifier network is also trained from scratch with a learning rate of 0.01 for 5 epochs.

IV. RESULTS

The experimental results are obtained by 5-fold cross validation and the focus of the experiments was two-fold:

- Analyzing the 3D pose estimation accuracy by comparing the results with a marker-based motion capture system as a reference.
- Analyzing the classification accuracies of the proposed system for detecting health problems.

A. 3D Pose Estimation Accuracy

The accuracy of the Pose Estimator network is measured by comparing the results with those obtained from a marker-based motion capture system (ground-truth) in terms of 3D pose error. 3D pose error is calculated based on the average of Euclidean distance between estimated 3D joints coordinates and corresponding ground-truth data for all joints. Averaged 3D pose errors are $36.12 \pm 17.41$ mm on the whole dataset. Table 1
shows the 3D pose error for each subject and group separately. Healthy group and Post Stroke group have the lowest and highest 3D pose error on the average, respectively.

1) Compare with Other Work

In order to be able to compare our results with the state-of-the-art methods for 3D human pose estimation, we applied our method on a public data set (Human3.6M [34]). Human3.6M is commonly used by researchers for 3D human pose estimation. It consists of 7 subjects and 15 different motions such as walking, sitting, posing, etc. Four RGB cameras record the subjects’ activities and a synchronized motion capture system measures their movement, which provides 3D ground truth joint coordinates. We follow the standard protocol of the dataset for a fair comparison and use subjects 1, 5, 6, 7, and 8 for training, and subjects 9 and 11 for testing. Results are presented in table 2. To the best knowledge of the authors, Pavlakos et al. [35] is the only work, which reported results for multi-view 3D pose estimation on Human36M dataset. As shown in table 2, we could achieve comparable results with them. However, Pavlakos et al. [35] employed the whole 2D pose heatmaps to estimate 3D joint coordinates, while we only use coordinates with highest probability (section III), which has lower dimensionality and makes the overall training time and model parameters significantly smaller. Other state-of-the-art methods presented in table 2 are for single view 3D pose estimation and our method achieves better performance than all of them. Comparing to the work by Martinez et al. [16], which use the same network design (except for the number of blocks, which is two instead of four) for single view 3D human pose estimation, we reduced the 3D pose error by about 9 mm on the average using our proposed multi-view fusion technique (section III).

B. Health Problem Classification Accuracy

Results for automatic health problem detection from the estimated 3D body pose time series is given in this section. Table 3 shows the confusion matrix and recall (sensitivity) values for each class. It is noticeable that classifying the healthy subjects was the easiest task for the proposed system and its recall is significantly higher than other classes. Only one False Positive case and one False Negative case happened, where one of the patients with Parkinson’s disease was misclassified as healthy, and one of the normal subjects was misclassified as a Pose Stroke patient. The rare False Positives and False Negatives in the proposed automatic system demonstrates the high confidence of the system for in-home gait monitoring of patients and elderly people. Moreover, the accuracy of detecting type of the health problem was 62.9% (26 misclassification out of 70 patients). Misclassification occurred between all the patients, but Orthopedic and Pose Stroke classes have the highest misclassification rate, where 8 out of 25 patients with Orthopedic problems were misclassified as Pose Stroke, and 5 out of 22 Post Stroke patients were misclassified as orthopedic patients (table 3).

In order to investigate the classification accuracy with respect to the health problem severity, Functional Ambulatory Category (FAC) level is used. FAC evaluates the ambulation ability of patients by determining the supports that patient requires for walking, with zero representing a patient who cannot walk or needs support from two or more people, and 5 representing a patient who can walk independently anywhere. Since the FAC values were not available for all the patients, only those with FAC information are included in this investigation. As shown in figure 4, no correlation between the classification accuracy and health problem severity was observed, as the average of FAC for both the correctly classified and misclassified patients were in the same range.

![Fig. 4. Classification accuracy with respect to the health problem severity. Vertical axes denotes Functional Ambulatory Category (FAC) level.](image-url)
1) Impact of Estimated 3D Pose on Classification Accuracy

In order to investigate the impact of the estimated 3D poses accuracy on the health problem classification accuracy, we use ground-truth 3D body pose time series (instead of estimated 3D body pose time series) and feed them to the Classifier network. Results are given in table 4. Compare to table 3, which reports the results for estimated 3D body pose series as the input, no changes in the False Positive rate can be observed, but False Negative rate has increases. Moreover, misclassification between health problem groups is reduced. In particular, the accuracy of detecting type of the health problem increases to 70% (21 misclassification out of 70 patients), which represents 11% improvement compare to using estimated 3D body pose time series as the input.

2) DNN vs SVM

In order to investigate the ability of the DNN for gait-related health problem classification, we compare the classification results with those obtained by SVM, which is one of the most commonly used machine learning methods for gait classification [20, 22, 23]. SVM is a feature-based classifier that constructs hyperplane boundaries by maximizing the margin between distinct classes. We repeat the same experiment by using concatenation of estimated 3D body pose time series as the input features for the SVM model. Results are given in table 5 and it is shown that both False Positive and False Negative cases increase from one case to 7 and 6 cases, respectively. Moreover, misclassification between health problem groups increase significantly and only 33 out of 70 patients were correctly classified (47.1 % accuracy). This indicates the capability of the proposed DNN for classification, which is due to the ability of the network to learn semantic and high level features from the input time series without further feature engineering.

### V. DISCUSSION

In this study, we developed an automatic system for detection of gait-related health problems for monitoring patients in their natural living environments and on a continuous basis. The time series of the user’s 3D body pose were estimated from videos using a DNN-based method. Then, estimated 3D body pose time series were analyzed and semantic and high level features were extracted for detecting a specific health problem.

The proposed system removes the requirement of complex equipment and large laboratory space, and does not need domain medical knowledge for feature engineering. Results showed that the proposed system is capable of detecting a
health problem with high confidence and safety (rare False Positive and False Negative) from only two digital cameras and it demonstrates potential of the proposed system for in-home gait monitoring of patients and elderly people.

Despite large amount of literatures devoted to binary gait classification for clinical application (healthy vs not-healthy) [21, 24, 36], multi-class gait classification is not well-studied. Compare to the binary gait classification, multi-class gait classification is more challenging, since it not only needs to recognize the abnormal gait pattern, but also should be able to differentiate between abnormalities. This is not a straightforward task due to the fact that neurological diseases that interfere with gait pattern display similarities in gait abnormalities including short steps, leg rigidity, and impaired posture [37]. A few studies explored the field of machine learning and proposed methods for multi-class gait classification in order to detect health problems from gait pattern, but these methods usually need high-end equipment e.g. optical motion capture systems [20] and IMU sensors [23] to capture body pose time series, which makes them impractical for in-home use.

In this study, DNN could achieve accurate 3D body pose estimation without complex setup and data processing procedures and by using only two digital cameras. Comparing to other state-of-the-art 3D body pose estimation methods, we reported comparable or better accuracy on Human3.6M dataset [34] by employing our proposed multi-view fusion technique (section III). Furthermore, results on our gait dataset showed that the proposed method is capable of estimating 3D body pose with high accuracy suitable for clinical application. The average of 3D body pose error was between 29.2 mm to 44.4 mm for different groups, where lowest error belonged to the Healthy group. This is somehow an expected result, since abnormal body posture and higher intra-subject variability of patients makes it more difficult for the network to estimate their body pose.

Comparing results of tables 3 and 4 shows that improving the 3D pose estimation accuracy results in increasing classification performance. Since estimating 3D body pose from images could be noisy and associate with error, it affects the classification accuracy. However, the classification performance degradation from estimated 3D body pose compare to ground-truth 3D body pose was not significant, which demonstrates robustness of the proposed classifier to some level of noises.

In contrast to previous studies that use traditional machine learning methods such as SVM for gait classification [20, 23], our proposed DNN based classifier does not require feature engineering on the body pose time series. In order to assess the performance of the proposed classifier, we compare the results with those obtained from SVM as one of the most common machine learning methods for gait classification. Results showed that the classification accuracy improves significantly by applying our DNN-based classifier (table 5). It happens due to the ability of the DNNs to learn semantic and high level features from time series, compare to traditional machine learning algorithms, which require feature engineering to define hand-crafted features and are usually associate with discarding a large amount of potentially meaningful information.

Moreover, analyzing of results revealed that Healthy group achieved the best classification accuracy, while the rest of the groups i.e. Post Stroke, Parkinson, and Orthopedic achieved comparable accuracies, which are significantly lower than Healthy group. Except for one False Negative and one False Positive case, all the misclassifications happened between the three pathology groups. This happens due to the fact that altered gait pattern can be similar between different pathologies and gait alteration due to injuries can be significantly affected by various events in the gait. Furthermore, no correlation was observed between the classification accuracy and health problem severity, however; the number of patients with available FAC values were limited and the range of available FAC values were small (mostly 3 and 4), which means that generalization of these results should be done with caution.

VI. CONCLUSION

In this study, we proposed a system for automatic recognition of gait-related health problems. Leveraging the advances of Deep Learning techniques, allowed for removing high-end equipment and laboratory space requirement and made the proposed system suitable for in-home use. The overall classification accuracy was 71%. Most of the misclassifications happened between the pathology groups, and only one False Positive and False Negative case was observed. The ultimate goal of our research is to provide an ambient-assisted living tool for gait monitoring of patient and elderly people in the domestic environment by taking advantages of DNNs. The present study can be considered as a starting point of the research along this direction and can be used as a basis for future applications of Deep Learning in clinical gait analysis and pathological gait diagnoses. Future works will focus on expanding the work by inclusion of other pathological populations and improving classification accuracy by adding joint kinetics time series to the Classifier input.

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