The 29^{th} ILP conference, 3–5 Sep 2019, Plovdiv, Bulgaria.

Explainable AI for Clinical Gait Analysis: Developing Diagnostics with Inductive Logic Programming

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Keywords: Medical Diagnostics · Gait Analysis · Inductive Logic Programming

1 Introduction

The motion of a human walker carries information about multiple attributes of the individual with many potential applications. Along with manifesting biologically intrinsic properties and personally identifiable attributes, one's gait also changes dynamically based on one's emotions [1] and state of health [2]. Of particular interest to the medical community is the manifestation in gait of neurodegenerative diseases, such as Parkinson's [3] and musculoskeletal disorders, e.g. osteoarthritis [4]. The corresponding changes are usually depicted as a deviation of established clinical gait metrics from normative ranges. In clinical practice, specific gait metrics [5] that describe the spatio-temporal aspects of gait per gait cycle are used for disease diagnosis, rehabilitation progress monitoring and evaluation of the physiotherapy intervention.

Human gait can be captured using a variety of body motion capture systems, however the result of the capture is represented as a multidimensional time series signal of the trajectories of the vital joints of the body. In a clinical setting, there are two popular ways of capturing body motion, marker-based and marker-less. Marker based systems use active or passive IR reflectors placed on predesignated points on the body and capture the IR light reflected using multiple calibrated overhead cameras to triangulate the three-dimensional position of each reflector. Clinically deployed examples include the Vicon(TM)[6] and OptiTrack (TM)[7] systems. Marker-less sensors capture 3D depth images and utilise computational techniques to isolate and label the joints in the human body. Microsoft Kinect v2 is a time of flight based RGB-D camera that captures the depth images and utilises decision trees trained on a combination of Histogram of Gradient and Histogram of Optical Flow (HOG-HOF) vectors of the depth image to identify a human body in the image and label the joints. Intel RealSense works in a similar fashion by capturing the depth image through stereoscopic vision. The captured gait is then further processed to extract the relevant clinical gait metrics for classification. This study focuses on the potential of Inductive Logic Programming (ILP) to classify gait from clinically relevant gait metrics taking gender identification as a proxy classification objective.

2 Background

There have been numerous investigations into the ability of machine learning models to recognise gender from gait. Based on the gait capture techniques, the approaches can be divided into 2D binary silhouette video based [8-11], and 3D motion capture of skeletal joints [12-16]. To the best of our knowledge, the use of ILP for gait classification has not been explored yet.

2D silhouette based gait videos are often model-based to fit a stick-figure to focus on the limb motion trajectories. For the purposes of the paper, model-free silhouettes are not considered, as they provide additional external cues for easy identification of gender (hair, clothes etc). Lee and Grimson [17] employ features from dynamic human silhouettes by dividing the silhouette into seven regions and fitting an ellipse to each region. The centroid, the aspect ratio of the major and minor axes of the ellipse, and the orientation of the major axis of the ellipse are taken as features. Yoo et al. [18] extract static features as a sequence set of 2D stick figures and utilize a SVM and an ANN as classifiers of choice. 26 hand-crafted features including cycle time, mean and standard deviations of joint angles, their displacements and their corresponding time derivatives were provided as inputs to the ANN. Cao et al. [13] proposed a new method which recognizes gender from static full body images, using Histogram of Oriented Gradients (HOG) as feature and Adaboost [19] and Random Forest Algorithms [20] as classifiers. The concept of Gait Energy Image (GEI) was introduced by Han and Bhanu [9] as a static representation of the dynamics of gait for individuals' identification. Shiqi et al. [15] utilized GEI in gender identification. As GEI is model-free, the most important features in recognition are hair style and chest, which are external cues and not inherent in the dynamic of gait itself.

The launch of affordable RGB-D cameras made it possible to extract the 3D depth map of a walking person without any body contact, making the sensor suitable for biometric and clinical gait analysis. Sivapalan et al. [11] proposed an extended version of the GEI to 3D using binary voxel volumes analogous to the 2D silhouettes, known as Gait Energy Volume (GEV). The study spatially aligned the voxels corresponding to the lower body averaged over a gait cycle. Borrás et al. [12] demonstrated that using 3D depth based features along with traditional 2D silhouette features led to a 6% rise in accuracy performance in gender identification from gait. The study of potential of gait analysis using 3D sensors is at an early stage compared to the maturity of 2D sensors.

While various machine learning techniques have achieved significantly high CCR, most models suffer from the black-box nature of their decisions, which is an issue in a medical setup. ILP techniques are white-box by nature hence our interest in them here.

3 Data and Background Knowledge

In this study, human gait is captured using a commercial grade Microsoft Kinect v2 RGB-D sensor. The gait is captured as a series of frames, each representing a human body pose, at 24 frames per second. The body pose is comprised of 3D trajectories of 20 joints of the body: head, neck, shoulders, elbows, wrists, fingertips, base of the spine, mid-spine, hips, knees, ankles and toes. Thirty-nine male and thirty-three female walkers participated in the experiment. Each walker walked on the treadmill at a self selected comfortable speed for four sessions. Each session comprises of a minute of walking followed by a minute of rest. The walkers walked in a well lit room with enough room on the treadmill belt for a natural walking pace. The gait was recorded as a multidimensional time series signal representing the positional trajectories of 20 joints of the body. All participants volunteered the data collection through written consent.

The collected data was visualised as a moving point dot animation labelled with gait events. The timestamp associated either foot lifting from the ground was demarcated as either a 'Left Foot Off' or a 'Right Foot Off' event. Either gait event signified the completion of a gait cycle. The gait events and the raw data were used to generate the gait metrics for the left, right and averaged values separately. The eight metrics in consideration are *Stride Length*, *Total Strides*, *Average Speed*, *Total Distance Travelled*, *Swing Stance Ratio*, *Average Cadence*, *Average Stride Length* and *Single Double Support Ratio*. In addition, the maximum acceleration for 14 joint angles and 3 trajectory deviations were derived per gait cycle. The median of the maximum acceleration was then used as feature in all cases.

The following relations have been encoded as background knowledge with the aim of extending the propositional data available and generating ILP models of gait:

L/R symmetry	Joints X and Y are/aren't on the same side of the body.
T/B symmetry	Joints X and Y are both above, resp. both below the waist.
Adjacency	Joint X is connected to joint Y (through a bone).
Same limb	Joints X and Y are on the same limb.

4 Discussion

While this work is still in progress, we can discuss how the ILP approach can help capture the peculiarities of gait associated with specific learning tasks beyond this particular data set. In the case of patients with stroke or asymmetric traumas, the limitations of one joint may be mirrored by another or compensated with its over-extended movement, while their relative position is characteristic of the condition or affected area in question. We have also conducted experiments with other patterns in the data, e.g. how the ratio of measurements associated with two joints compares with the golden ratio, 1.618.

References

1. Pollick, F. E., et al. *Estimating the efficiency of recognizing gender and affect from biological motion.* Vision research 42.20 (2002): 2345-2355.

2. Cesari, M., et al. *Prognostic value of usual gait speed in wellfunctioning older peopleresults from the Health, Aging and Body Composition Study.* Journal of the American Geriatrics Society 53.10 (2005): 1675-1680.
3. Morris, M. E., et al. *The biomechanics and motor control of gait in Parkinson disease.* Clinical biomechanics 16.6 (2001): 459-470.
4. Kaufman, K. R., et al. *Gait characteristics of patients with knee osteoarthritis.* Journal of biomechanics 34.7 (2001): 907-915.
5. Sosnoff, J. J., Sandroff, B. M., and Motl, R. W. *Quantifying gait abnormalities in persons with multiple sclerosis with minimal disability.* Gait & posture 36.1 (2012): 154-156.
6. Windolf, M., Gtzen, N., and Morlock, M. *Systematic accuracy and precision analysis of video motion capturing systemsexemplified on the Vicon-460 system.* Journal of biomechanics 41.12 (2008): 2776-2780.
7. Carse, B., et al. *Affordable clinical gait analysis: An assessment of the marker tracking accuracy of a new low-cost optical 3D motion analysis system.* Physiotherapy 99.4 (2013): 347-351.
8. Barclay, C. D., Cutting, J. E., and Kozlowski, L. T. *Temporal and spatial factors in gait perception that influence gender recognition.* Perception & psychophysics 23.2 (1978): 145-152.
9. Han, J., and Bhanu, B. *Individual recognition using gait energy image.* IEEE transactions on pattern analysis and machine intelligence 28.2 (2006): 316-322.
10. Pollick, F. E. *The features people use to recognize human movement style.* International Gesture Workshop. Springer, Berlin, Heidelberg, 2003.
11. Sivapalan, S., et al. *Gait energy volumes and frontal gait recognition using depth images.* 2011 International Joint Conference on Biometrics (IJCB). IEEE, 2011.
12. Borrás, R., Lapedriza, À., and Igual, L. *Depth information in human gait analysis: an experimental study on gender recognition.* International Conference Image Analysis and Recognition. Springer, Berlin, Heidelberg, 2012.
13. Cao, L., et al. *Gender recognition from body.* Proceedings of the 16th ACM international conference on Multimedia. ACM, 2008.
14. Davis, J. W., and Gao, H. *An expressive three-mode principal components model for gender recognition.* Journal of Vision 4.5 (2004): 2-2.
15. Shiqi, Y., et al. *A study on gait-based gender classification.* IEEE Transactions on image processing 18.8 (2009): 1905-1910.
16. Ma, Y., Paterson, H. M., and Pollick, F. E. *A motion capture library for the study of identity, gender, and emotion perception from biological motion.* Behavior research methods 38.1 (2006): 134-141.
17. Lee, L., and Grimson, W. E. L. *Gait analysis for recognition and classification.* Proceedings of Fifth IEEE International Conference on Automatic Face Gesture Recognition. IEEE, 2002.
18. Yoo, J., Hwang, D., and Nixon, M. S. *Gender classification in human gait using support vector machine.* International Conference on Advanced Concepts for Intelligent Vision Systems. Springer, Berlin, Heidelberg, 2005.
19. Rtsch, G., Onoda, T., and Mller, K-R. *Soft margins for AdaBoost.* Machine learning 42.3 (2001): 287-320
20. Pal, M. *Random forest classifier for remote sensing classification.* International Journal of Remote Sensing 26.1 (2005): 217-222.