Visualization of interindividual differences in spinal dynamics in the presence of intraindividual variabilities

Conference Paper · April 2022

DOI: 10.36730/2022.1.levia.6

11 authors, including:

Carlo Dindorf
Technische Universität Kaiserslautern

Jürgen Konradi
Universitätsmedizin der Johannes Gutenberg-Universität Mainz

Claudia Wolf
Johannes Gutenberg-Universität Mainz

Bertram Taetz
IU International University of Applied Sciences

Visualization of interindividual differences in spinal dynamics in the presence of intraindividual variabilities

Carlo Dindorf*, Jürgen Konradi†, Claudia Wolf†, Bertram Taetz‡, Gabriele Bleser‡,
Janine Huthwelker†, Friederike Werthmann§, Eva Bartaguiz*, Philipp Drees§, Ulrich Betz† and Michael Fröhlich*

*Department of Sports Science, TU Kaiserslautern, Kaiserslautern, Germany
E-mail: carlo.dindorf@sowi.uni-kl.de

†Institute of Physical Therapy, Prevention and Rehabilitation, University Medical Centre of the JGU Mainz, Mainz, Germany

‡Department Augmented Vision, German Research Center for Artificial Intelligence, Kaiserslautern, Germany

§Department of Orthopedics and Trauma Surgery, University Medical Centre of the JGU Mainz, Mainz, Germany

***Abstract*—Surface topography systems enable the capture of spinal dynamic movement. A visualization of possible unique movement patterns appears to be difficult due to large intra-class and small inter-class variabilities. Therefore, we investigated a visualization approach using Siamese neural networks (SNN) and checked, if the identification of individuals is possible based on dynamic spinal data. The presented visualization approach seems promising in visualizing subjects in the presence of intraindividual variability between different gait cycles as well as day-to-day variability. Overall, the results indicate a possible existence of a personal spinal 'fingerprint'. The work forms the basis for an objective comparison of subjects and the transfer of the method to clinical use cases.**

***Index Terms*—Siamese Neural Networks, triplet loss, contrastive loss, surface topography, subject identification**

I. INTRODUCTION

Biometric person identification is an important research field that has many practical applications, with the general aim of identifying persons based on unique biological characteristics. Machine Learning has gainted increasing interest in the gait research domain and several works have demonstrated the utility of human gait for subject identification [17], [19], [35]. Regarding health-related sectors, subject identification and the determination of similarities between subjects are of high research interest, as are longitudinal comparisons of subjects over time [20], [36]. However, large intra-class and small inter-class variations of the human gait pose significant challenges [19], [28]. Further, the amount of available clinical data is often limited.

As a methodological approach for the respective characterstics, deep metric learning via Siamese Neural Networks (SNN), a special type of neural network, has showed promising results. SNN were able to learn from only few or even only one training sample (one shot learning) of each class, respectively [2]. The general aim is to put different samples further apart from each other and similar samples nearer to each other by learning discriminative embeddings [16]. Previous works demonstrated, that SNN were able to extract meaningful, robust and discriminative gait features [19], [33], [35], which forms the basis for visualization, identification as well as determination of similarities.

SNN were mainly applied in the field of computer vision (e.g. [12]). Several clinical and health related studies can be found in the literature (similarities of patients from electronic health records [34]; disease severity evaluation and change detection retinopathy of prematurity in retinal photographs and osteoarthritis in knee radiographs [22]; prediction symptomatic progression Alzheimer's disease [1], automatic tracking of the lumbar spine [23], and detection of brain asymmetries [24]). To the best knowledge of the authors, the utility of SNN in the context of biomechanical waveform data has not been analyzed so far.

Therefore, our aim is to evaluate feature learning approaches using SNN for reducing intra-class and increasing inter-class variability for visualization of individual movement patterns of the spine.

II. METHOD

A. Measuring method, subjects, and data

The DIERS formetric III 4DTM, DICAM v3.7.1.7 was used to capture dynamic spinal movement by means of surface topography (ST). The system works without exposure to radiation, which is particularly advantageous since repeated scans are possible without any undesirable effects on human health [3], [31]. Furthermore, it can be used in a relatively time-efficient manner and potential sources of error can be

The presented abtract is based on a previously published work by [8].
Dataset B is part of the dissertation project of Friederike Werthmann.
LEVIA'20: Leipzig Symposium on Visualization in Applications 2022

reduced, since only a few markers have to be set. In addition, no particularly complex training of the staff is required, since the measurements are relatively easy to carry out. Apart from the need for dynamic recordings to be carried out on the treadmill, the test persons are not directly influenced in their natural gait behavior during the measurements.

The light-optical measurement of the back with the system is based on (video) rasterstereography. Figure 1 shows the system and the rough course of a measurement. For a measurement, a light grid is first projected onto the textile-free back of the test person using a projector and recorded with a camera unit (60 Hz). The raster slide is built into the projector and forms the stereo image pair together with the camera image. Based on the curvature of the line, a three-dimensional image of the surface topography of the back is generated in accordance with photogrammetry. The reconstructed dorsal surface is first described as 3D point coordinates (x,y,z), which depend on the subject's position relative to the camera. Therefore, invariant shape parameters (convex, concave, saddle-shaped) are determined, which are independent of the relative position in space. The position in relation to the camera or the rotation around the longitudinal body axis should therefore have no influence on the results [5]. Based on this, anatomical structures (vertebra prominens, lumbar dimples) are determined from which further points can be derived mathematically (e.g. the middle between the lumbar dimples). Based on this information, conclusions can then be drawn about the skeleton geometry including corresponding 3D movements from the vertebra prominens (C7) down to L4 and the pelvis. This is based on a correlation model according to Turner-Smith [30] and Drerup [4], which describes the relationship between the surface curvature of the body and the alignment of the vertebras.

The data used contained measurements from 201 (Dataset A) and 25 (Dataset B) healthy subjects (132/13 female, 69/12 male) while walking (2 and 4 km/h). The Dataset B group was measured on three different days (Day 1, Day 2, and 30 ± 7 days later). The reference data was approved by the responsible ethics committee of the Medical Chamberof Rhineland-Palatinate (837.194.16, 2018-13607-Klinische Forschung) and registered with WHO (INT: DRKS00010834, DRKS00014325). Missing data points were interpolated using spline interpolation (maximum gap = 5 frames). Cycles with remaining gaps were dropped. Afterwards, the gait cycles were individually time-normalized to 101 time steps (from 0% to 100%) using cubic spline interpolation. Figure 2 shows an example of the time-normalized movement patterns of two vertebras during a gait cycle.

B. Feature extraction and visualization

Dataset A was used for model training, Dataset B was used for testing. This split was chosen because it allows the model performance to be evaluated in the presence of day-to-day variability (Dataset B). The reference data pool for testing was formed by the measurements of the first and second day for Dataset B as well as the samples of Dataset A. The measurements on day three of Dataset B were used for testing. Similar to previous works [9], [27], concatenated waveform data was used as input features for the automatic feature extraction. Deep metric learning was performed using Siamese Neural Networks using contrastive loss [14] and triplet loss [32] as loss functions for optimization. A Multilayer Perceptron Feedforward Neural Network (MLP) was selected with two hidden layers. The network architecture of the multilayer perceptron feedforward neural network and the hyperparameters were determined manually (5555-neuron input layer; 1000-neuron hidden layer 1; 100-neuron hidden layer 2; 5-neuron output layer; rectified linear activation function, Adam optimizer). The same network architecture was used for comparing the use of the contrastive loss to the triplet loss function.

TABLE I

RESULTS OF THE TOP FIVE EXTRACTED FEATURES USING THE THREE APPROACHES. RANGE OF MOTION (ROM), MINIMA (MIN), AND MAXIMA (MAX) REPRESENT THE FEATURE EXTRACTION USING SIMPLE DESCRIPTIVE STATISTICS.

	Contrastive Loss	**Triplet Loss**	**ROM, Min, Max**
Validation set accuracy	100.00 % True: 402 False: 0	96.52 % True: 388 False: 14	95.02 % True: 382 False: 20
Test set accuracy	96.00 % True: 144 False: 6	85.33 % True: 128 False: 22	82.00 % True: 123 False: 27

The results were compared with those using extracted features based on an extraction using simple descriptive statistics. Therefore, in the literature commonly applied operations (e.g. [7], [29]) were used (range of motion, minima, and maxima). For comparing feature subsets of the same size, sequential forward selection using Euclidean distance for subject identification was applied for ranking and selecting a feature subset of the features based on simple descriptive statistics. The number of selected features was set as equal to the fife. The input feature sets were separately scaled to a range between zero and one based on the training data.

Based on the extracted features, subject identification was performed for further evaluation using Euclidean distance. Therefore, the data sample in the reference pool with the lowest distance was predicted as the person to be identified.

Finally, visualization of the learned discriminative embeddings was performed plotting the test subjects in a 2D space after doing dimensionality reduction on the extracted features with t-SNE [26].

III. RESULTS

Figure 3 shows the visualizations of the test set subjects in a 2D space before and after performing feature extraction. A separation between the subjects is observable. For example, for the subjects C, G, and S, the respective gait cycles were closer together compared to the t-SNE visualization of the concatenated waveform data before the feature extraction.

Classification results are presented in Table 1. For the test data, 100 % accuracy was obtained using the concatenated

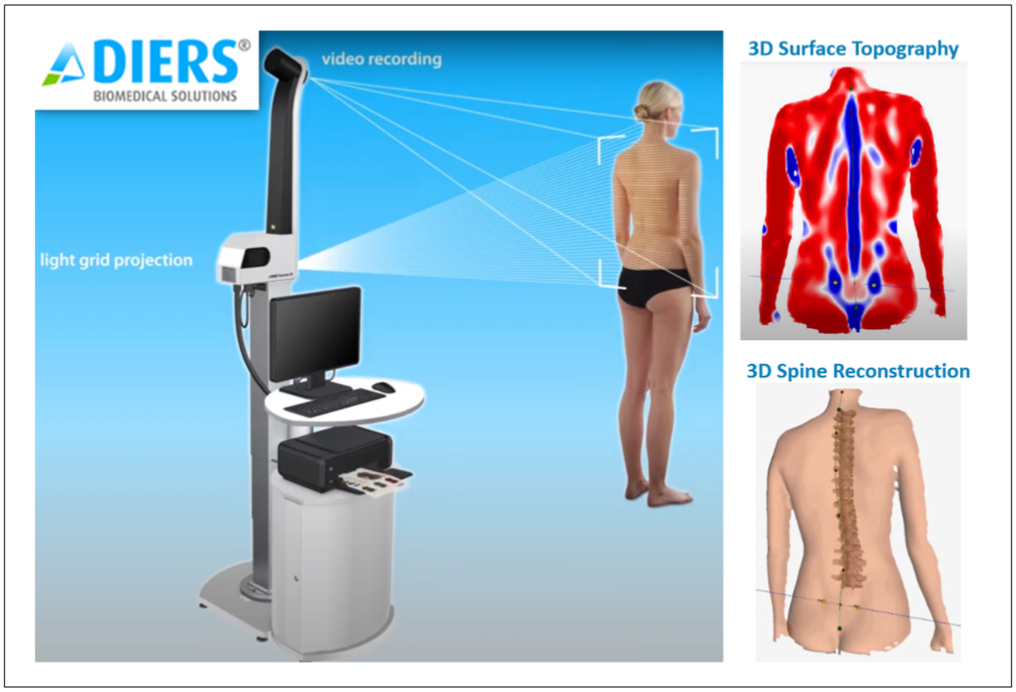

Fig. 1. Schematic measurement procedure using the DIERS formetric system used in the MotionLab of the University Medical Centre of the JGU Mainz, Germany. Image kindly provided by DIERS International GmbH.

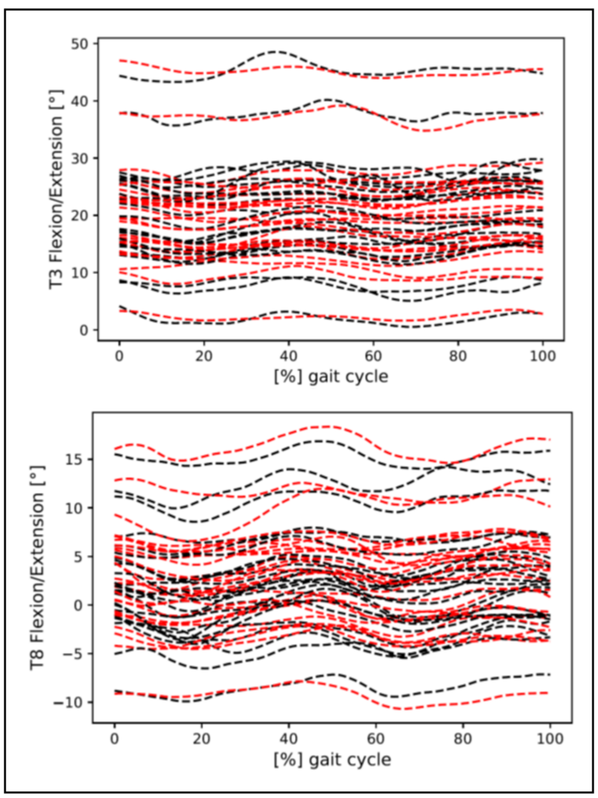

Fig. 2. Exemplary visualization of the time-normalized sequence data for T3 and T8 movement in the sagittal plane of the 25 test subjects. For every test subject, one measurement of each walking speed is displayed. black = 2 km/h, red = 4 km/h

waveform data without performing feature extraction. The test set accuracy was slightly reduced after the feature extraction. The highest accuracy was present with the SNN using the contrastive loss function, followed by the SNN with triplet loss.

IV. Discussion

The current study shows that the identification of individuals based on dynamic movement patterns of the spine is possible. The extracted features, especially for use with an SNN with contrastive loss, seemed to reduce intraindividual variability and make subjects more distinct. This is also surprising, as the gait cycles of each subject were recorded at two different speeds. In this way, the extracted features should map movement patterns of the spine that show little variance or are invariant over different gait cycles, speeds, and measuring days. This results in a higher similarity between the gait cycles per subject as well as better separation between the subjects in the presented visualization.

Using extracted features, the accuracy was slightly reduced compared to the use of the entire concatenated waveforms. However, feature extraction is an important step toward improving interpretability and the model's accuracy, and for preventing overfitting and reducing the computing power [21]. Based on the huge amount of data, direct interpretation of the dynamic spinal data is hardly possible for humans. In line with a previous study [7], a clinically relevant interpretation is only adequately possible through the extraction of meaningful features. If not only classification but also reduction of intraindividual variabilities, visualization as well as identification

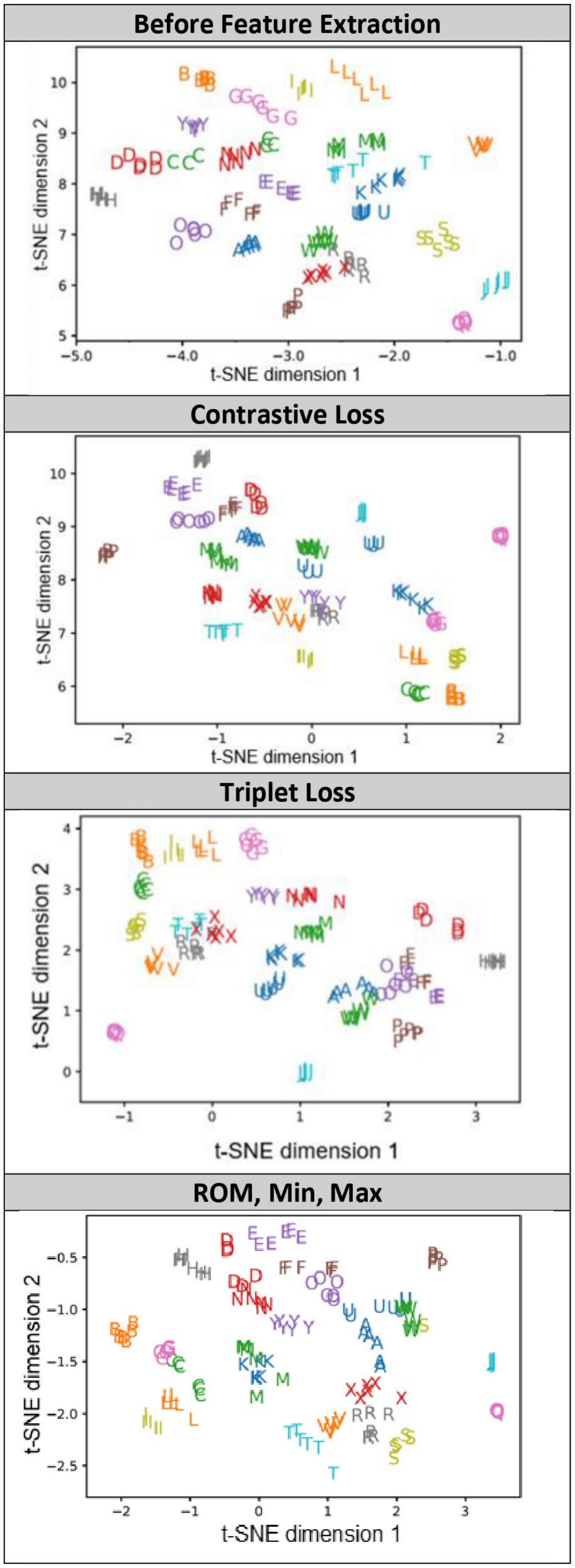

Fig. 3. Visualization of the test set subjects in a 2D space before and after performing t-SNE on the representations of the feature extraction approach using the Siamese neural networks with contrastive loss function. The color code as well as the different alphabetic characters map the individuals.

of individual movement patterns is important, a slight drop in classification performance seems reasonable to achieve the other goals.

Contrary to this study, previous research showed that an SNN with triplet loss could learn better representations compared to an SNN with contrastive loss [15]. Possible reasons for the present results might be that the network architecture was predetermined using contrastive loss and, therefore, was not optimal for use with triplet loss. Furthermore, choosing difficult triplet could be an essential step for further increasing the model's performance [13]. Future research should consider and compare other network architectures, e.g. recurrent neural networks or 1D convolutional neural network models in the context of waveform data. As a promising alternative to the t-SNE algorithm, the use of Uniform Manifold Approximation and Projection (UMAP) [25] should be considered for future works. Also, model interpretation using Explainable Artificial Intelligence (XAI) should be considered for the precise identification of individual regions of the waveform data, which are important for the identification task [6], [10]. Finally, the inclusion of thermographic data should be considered, as these can map aspects of the spine [18] as well as muscular factors [11].

Regarding the comparison of healthy subjects and patients, absolute group assignments often shorten the facts. The application of the visualization approach and the determination of similarity scores in health and patient data could be useful for monitoring progress (e.g. during rehabilitation) or continual changes.

V. Conclusion

Overall, the presented visualization approach seems promising in visualizing subjects in the presence of intraindividual variability between the gait cycles of one day recorded at different speeds as well as day-to-day variability. Finally, the results indicate a possible existence of a personal spinal 'fingerprint'. A possible field of application is the monitoring or detection of longitudinal changes (in physiology) in subjects.

Funding

This work was supported by the BMBF, under grant numbers 16SV7115 and 03IHS075B, and from funds of the intramural research funding for third-party funded projects of the University Medicine of the JGU Mainz.

REFERENCES

[1] N. Bhagwat, JD. Viviano, AN. Voineskos and MM. Chakravarty. “Modeling and prediction of clinical symptom trajectories in Alzheimer’s disease using longitudinal data,” PLoS Comput Biol., vol. 14, no. 9, pp. 1–25, 2018, doi: https://doi.org/10.1371/journal.pcbi.1006376

[2] D. Chicco. “Siamese neural networks: An overview,” Methods in molecular biology, vol. 2190, pp.73–94, 2021, doi: 10.1007/978-1-0716-0826-5_3

[3] J. Chowańska, T. Kotwicki and K. Rosadziński, “Comparison of standing and sitting position used in surface topography trunk assessment,” Postepy Nauk Medycznych, vol. 25, no. 6, pp. 476–483, 2012.

[4] B. Drerup and E. Hierholzer, “Back shape measurement using video rasterstereography and three-dimensional reconstruction of spinal shape,” Clinical Biomechanics, vol. 9, no. 1, pp. 28–36, 1994. doi: 10.1016/0268-0033(94)90055-8.

[5] B. Drerup, B. Ellger, F. M. Meyer zu Bentrup and E. Hierholzer, “Rasterstereographische Funktionsaufnahmen. Eine neue Methode zur biomechanischen Analyse der Skelettgeometrie,” Der Orthopäde, vol. 30, no. 4, pp. 242–250, 2001, doi: 10.1007/s001320050603.

[6] C. Dindorf et al., “Towards a better understanding of spinal differences between healthy subjects and subjects with back pain using Explainable Artificial Intelligence (XAI),” in Proceedings of the 9th International Performance Analysis Workshop and Conference & 5th IACSS Conference, A. Baca, J. Exel, M. Lames, N. James, N. Parmar, Eds., Springer: Vienna, Austria , 2021, pp. 30-31 doi: 10.1007/978-3-030-99333-7_16

[7] C. Dindorf et al., “Feature extraction and gait classification in hip replacement patients on the basis of kinematic waveform data,” Biomedical Human Kinetics, vol.13, no. 1, pp. 177-186, 2021, doi: 10.2478/bhk-2021-0022

[8] C. Dindorf et al., “Machine learning techniques demonstrating individual movement patterns of the vertebral column: The fingerprint of spinal motion,” Comput. Methods Biomech. Biomed. Engin., pp. 1–11, 2021, doi: 10.1080/10255842.2021.1981884.

[9] C. Dindorf, W. Teufl, B. Taetz, G. Bleser, and M. Fröhlich, “Interpretability of Input Representations for Gait Classification in Patients after Total Hip Arthroplasty,” Sensors, vol. 20, no. 16, 2020, doi: 10.3390/s20164385.

[10] C. Dindorf et al., “Classification and Automated Interpretation of Spinal Posture Data Using a Pathology-Independent Classifier and Explainable Artificial Intelligence (XAI),” Sensors, vol. 21, no. 18, 2021, doi: 10.3390/s21186323.

[11] C. Dindorf, E. Bartaguiz, E. Janowicz, M. Fröhlich and O. Ludwig, “Effects of Unilateral Muscle Fatigue on Thermographic Skin Surface Temperature of Back and Abdominal Muscles—A Pilot Study,” Sports (Basel, Switzerland), vol. 10, no. 3, pp. 1–10, 2022. doi: 10.3390/sports10030041.

[12] G. Figueroa-Mata and E. Mata-Montero, “Using a convolutional siamese network for image-based plant species identification with small datasets,” Biomimetics (Basel). vol. 5, no 1, p. 8, 2020, doi: 10.3390/biomimetics5010008

[13] A. Gordo, J. Almazan, J. Revaud, and D. Larlus, “Deep Image Retrieval: Learning global representations for image search,” 2016. [Online]. Available: http://arxiv.org/pdf/1604.01325v2

[14] R. Hadsell, S. Chopra, and Y. LeCun, “Dimensionality Reduction by Learning an Invariant Mapping,” in CVPRW ’06: 2006 Conference on Computer Vision and Pattern Recognition Workshop : 17-22 June 2006, New York, NY, USA, 2006, pp. 1735–1742.

[15] E. Hoffer and N. Ailon, Deep Metric Learning using Triplet Network. 2015. [Online]. Available: https://arxiv.org/pdf/1412.6622.pdf

[16] R. Hadsell, S. Chopra and Y. LeCun. “Dimensionality reduction by learning an invariant mapping,” In: IEEE 2006. Computer Society Conference on Computer Vision and Pattern Recognition (CVPR’06); 17- 22 June 2006; New York (NY). New York: IEEE; Vol. 2, pp. 1735–1742.

[17] A. Kececi, A. Yildirak, K. Ozyazici, G. Ayluctarhan, O. Agbulut, and I. Zincir, “Implementation of machine learning algorithms for gait recognition,” Engineering Science and Technology, an International Journal, vol. 23, no. 4, 2020, doi: 10.1016/j.jestch.2020.01.005.

[18] R. Koprowski, “Automatic analysis of the trunk thermal images from healthy subjects and patients with faulty posture,” Computers in Biology and Medicine, vol. 62, pp. 110–118, 2015. doi: 10.1016/j.compbiomed.2015.04.017.

[19] W. Liu, C. Zhang, H. Ma, and S. Li, “Learning Efficient Spatial-Temporal Gait Features with Deep Learning for Human Identification,” Neuroinformatics, vol. 16, no. 3-4, pp. 457–471, 2018, doi: 10.1007/s12021-018-9362-4.

[20] M. D. Li et al., “Siamese neural networks for continuous disease severity evaluation and change detection in medical imaging,” NPJ digital medicine, vol. 3, p. 48, 2020, doi: 10.1038/s41746-020-0255-1.

[21] H. Liu, L. Yu, “Toward integrating feature selection algorithms for classification and clustering,” IEEE Trans Knowl Data Eng, vol. 17, no. 4, pp. 491–502, Apr. 2005, doi: 10.1109/TKDE.2005.66.

[22] M.D. Li et al., “Siamese neural networks for continuous disease severity evaluation and change detection in medical imaging,” npj Digital Medicine, vol. 48, no. 3, pp. 1–9, 2020, doi: 10.1038/s41746-020-0255-1

[23] Y. Liu, X. Sui, C. Liu, X. Kuang and Y. Hu, “Automatic lumbar spine tracking based on Siamese convolutional network,” J Digit Imaging, vol. 33, no. 2, pp. 423–430, 2019, doi: 10.1007/s10278-019-00273-5

[24] C-F. Liu et al., “Using deep Siamese neural networks for detection of brain asymmetries associated with Alzheimer’s disease and mild cognitive impairment,” Magn Reson Imaging, vol. 64, pp. 190–199, Jul 2019, doi: 10.1016/j.mri.2019.07.003

[25] L. McInnes, H. John and J. Melville. ”Umap: Uniform manifold approximation and projection for dimension reduction,” 2018. doi: 10.48550/arXiv.1802.03426

[26] L. van der Maaten and G. Hinton, “Visualizing Data using t-SNE,” Journal of Machine Learning Research, vol. 9, pp. 2579–2605, 2008.

[27] D. Slijepcevic et al., “Explaining Machine Learning Models for Clinical Gait Analysis,” ACM Trans. Comput. Healthcare, vol. 3, no. 2, pp. 1–27, 2021, doi: 10.1145/3474121.

[28] S. Tong, Y. Fu, and H. Ling, “Verification-based pairwise gait identification,” in 2017 IEEE International Conference on Multimedia & Expo workshops (ICMEW): Hong Kong, 10-14 July 2017, pp. 669–673.

[29] W. Teufl et al “Automated detection and explainability of pathological gait patterns using a one-class support vector machine trained on inertial measurement unit based gait data,” Clinical Biomechanics, vol. 89, 105452, Aug. 2021 doi: 10.1016/j.clinbiomech.2021.105452

[30] A. R. Turner-Smith, J. Harris, G. R. Houghton and R. J. Jefferson, “A method for analysis of back shape in scoliosis,” Journal of Biomechanics, vol. 21, no. 6, pp. 497–509, 1988. doi: 10.1016/0021-9290(88)90242-4.

[31] A. Truszczynska, “Measurement of spinal curvatures during sitting on a rehabilitation ball versus stool,” Türkiye Fiziksel Tıp ve Rehabilitasyon Dergisi, vol. 62, no. 2, pp. 148–155, 2016. doi: 10.5606/tftrd.2016.10734.

[32] K. Q. Weinberger and L. K. Saul, “Distance Metric Learning for Large Margin Nearest Neighbor Classification,” Journal of Machine Learning Research, vol. 10, pp. 207–244, 2009.

[33] Z. Wu, Y. Huang, L. Wang, X. Wang and T. Tan, “A comprehensive study on cross-view gait based human identification with deep CNNs,” IEEE Trans Pattern Anal Mach Intell, vol. 39, no. 2, pp. 209–226, 2009

[34] F. Zhao, J. Xu and Y. Lin, “Similarity measure for patients via a Siamese CNN network”. In: Algorithms and architectures for parallel processing, J. Vaidya and J. Li, Eds. Cham: Springer International Publishing; pp. 319–328, 2018

[35] C. Zhang, W. Liu, H. Ma, and H. Fu, “Siamese neural network based gait recognition for human identification,” in 2016 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), Shanghai, Mar. 2016 - Mar. 2016, pp. 2832–2836.

[36] F. Zhao, J. Xu, and Y. Lin, “Similarity Measure for Patients via A Siamese CNN Network,” in Lecture notes in computer science, Algorithms and Architectures for Parallel Processing, J. Vaidya and J. Li, Eds., Cham: Springer International Publishing, 2018, pp. 319–328.