Anusandhanvallari
Vol 2025, No.1
December 2025
ISSN 2229-3388

Automatic Detection of Musculoskeletal Deformities Using Gait Biomechanics and Deep Learning: A Comprehensive Review

Shweta Shorey

Assistant Professor, MMH College, Model Town (West), Ghaziabad shweta.shorey@gmail.com

Abstract

Human gait can be analyzed as an essential point of view of musculoskeletal and nervous systems functionality. Gait abnormalities are the initial measurable factors of pathology including Cerebral Palsy (CP) and a spinal cord injury. The gait analysis has historically moved forward, replacing the subjective visual observation of the gait to an objectively quantitative lab test comparing lab standards of lab-based kinematic and kinetic measurements. But, the recent intersection of wearable sensor technology and Deep Learning (DL), has triggered a paradigm shift, where automatic, non-invasive and continuous detection of musculoskeletal deformities is enabled. The current paper is a thorough review of the literature aimed at analyzing the progression of the models of traditional kinematic algorithms and force-plate methodologies to the advanced ones based on Convolutional Neural Networks (CNNs) and neuro-fuzzy systems. Combining the information of all the studies used through the overground and treadmill locomotion, we assess the effectiveness of several biomechanical parameters, including the timing of the heel-strike and the toe-off, in the diagnosis of clinical conditions. The review focuses on the evolution of threshold-based heuristic algorithms to data-driven deep learning models that can extract latent features at the inertial measurement units (IMUs), and concludes that the combination of deep learning and biomechanical profiling can be the future of accuracy in orthopedic and rehabilitation diagnostic procedures.

Keywords: Gait biomechanics, musculoskeletal deformities, deep learning, motion analysis, automated diagnosis.

1. Introduction

Neurological disorders and musculoskeletal deformities are common changes that come with different modifications in human locomotion. Walking is a complex operation which involves the combination of neural orders, muscle contraction, and skeletal leverage. When this system is impaired by some system impairment as Cerebral Palsy (CP), stroke, or structural deformities, the end result is gait patterns that indicate important diagnostic data, including toe-walking, crouch gait, or asymmetry. As a result, the automatic identification of such gait events and the ensuing identification of deformities are now top-work topics in biomedical engineering, as well as clinical rehabilitation.

Historical gait analysis The classical gait analysis method used used complicated optoelectronic systems and force plates, restricted to motion laboratories. Although, they are very precise, these techniques are costly, time consuming and restricted to the spatial limits of the laboratory set-up (Davis et al., 1991; Kadaba et al., 1990). Kinematic algorithms (dependent on motion capture data) were investigated to develop more accessible and ecological assessment (Zeni et al., 2008; Hreljac and Marshall, 2000) and subsequently the use of wearable inertial sensors became popular (Yang and Hsu, 2010).

Anusandhanvallari
Vol 2025, No.1
December 2025
ISSN 2229-3388

The raw data produced by them are however very high dimensional and dense. Conventional signal processing methods are typically unable to capture the huge individual differences in pathological gait, even when repeated in different locations such as treadmills as compared to overground walking (Alton et al., 1998; Dingwell et al., 2001). Machine Learning (ML) and Deep Learning (DL) interventions have become the way out of this limitation. Since primitive neural networks (Miller, 2009) to more advanced Deep Convolutional Neural Networks (Hannink et al., 2017), artificial intelligence comes with the ability to hierarchically encode gait straight out of sensor data, without the electrical engineering of feature representations required. This paper will examine the theoretical and practical environment of automatic gait detection. We start with laying down the biomechanical principles and the variation in measurement conditions. We go on to criticize conventional deterministic gait event detection algorithms. We then consider the emergence of wearable sensors and deep learning architecture uses in decoding these sensors. Lastly, we report on the particular clinical applications, involving CP and spinal cord injuries, to show how these technologies are already identifying musculoskeletal deformities.

2. Biomechanical Foundations and Measurement Modalities

In order to automate the process of detecting the deformities, it is necessary to specify the parameters of normal and pathological gait to start with. Gait cycle is usually segmented into stance and swing phases, which are separated by certain events: Initial Contact (IC), commonly known as Heel Strike (HS), and Toe-Off (TO).

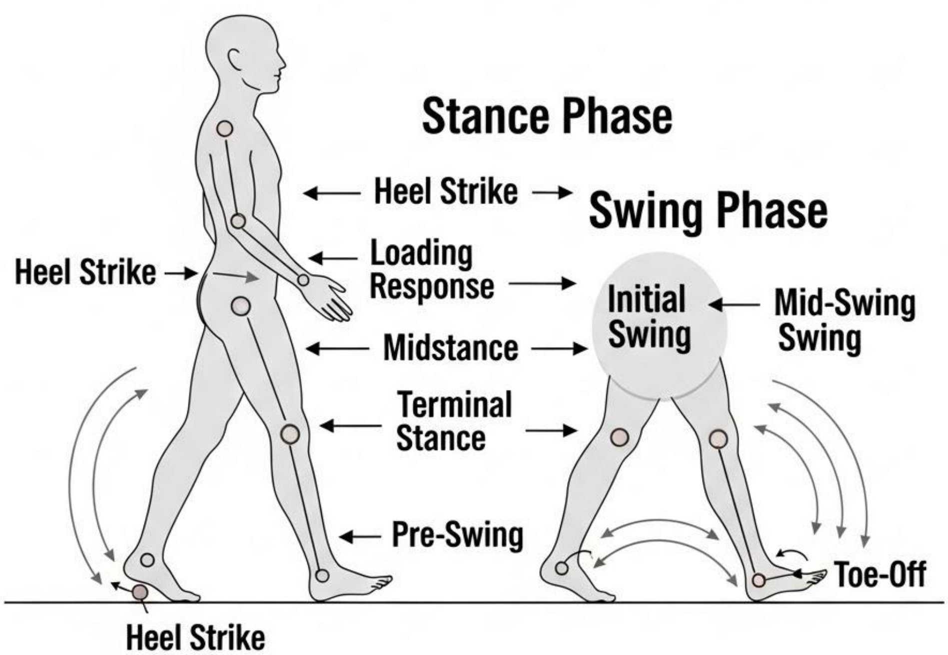

Figure 1: The standard human gait cycle, illustrating the progression from Initial Contact (Heel Strike) to Toe-Off. Pathological deviations often manifest as temporal or spatial disruptions within these specific phases.

2.1 The Laboratory Standard: Kinematics and Kinetics

The protocols of gait data collection and reduction were laid out by Davis et al. (1991) and Kadaba et al. (1990). The clinical routine gait analysis is based on retro-reflective markers introduced at the anatomical landmarks to model the lower extremity parts. Kadaba et al. (1990) showed that sagittal plane movement (flexion/extension) intra-subject repeatability is high, whereas transverse plane movement (rotation) is vulnerable to error measured by the skin skin artifact and a variable marker position.

Knowledge of these kinematic baselines is vital since musculoskeletal deviations tend to be manifested in the defective trend of these particular paths. An example of this is a child who has the equinus deformity (toe-walking) will not have the dorsiflexion that he needs to have a heel first initial contact. Gait event detecting algorithms should be strong enough to process such pathological ones, and this was a difficulty observed by Hsue et al. (2007) in their experiment involving children with CP.

2.2 Environmental Constraints: Overground vs. Treadmill Locomotion

An important controversy in the biomechanics literature that has an influence on the treadmill and overground training data used to train deep learning models is whether treadmill and overground walking can be interchanged. When an algorithm is being trained using treadmill data, will it be able to detect flaws in a known real-life context?

A kinematic comparison of the study by Alton et al. (1998) showed that there were significant differences. In their research, they found that when subjects were put on the treadmill balance and made to walk, they showed more hip flexion and also showed clear variation in knee kinematics when changes were compared with the same condition of walking on the ground. This implies that a changed sensory feedback loop is created by the mechanical limitations of the treadmill belt, and a distinct gait approach is acquired.

On the same note, Schache et al. (2001) examined three dimensional physiology of the lumbo-pelvic-hip complex during running. They discovered that the overall patterns of the waveforms were similar although statistically there was a difference in the magnitude of the movements with the frontal and transverse planes being the most noticeable. To detection algorithms, this means that a normal range of movement when in a treadmill could be considered abnormal when on the ground or the reverse which could cause a false positive result of the deformity detection.

Dingwell et al. (2001) took an alternative view of this that is dynamic stability. They discovered that local dynamic stability was quite different though there was no significant variation in the variability of the kinematics in the two modes. Locally, the subjects were more stationary on the treadmill probably because of the constant speed signal by the belt. This has tremendous effects on the automatic detection systems; programs that identify ataxia or instability abominations may be unable to diagnose patients effectively when they are running on a treadmill only.

The process of defining footstrike and toe-off in the process of running was further complicated by Fellin et al. (2010) who compared the methods of measuring it. They observed that the technique of detection (kinematic vs. kinetic) interacts with the mode of locomotion. So, the domain shift between laboratory treadmills and the real-life setting of patients should be explicitly considered in any deep learning model suggested to be used in a clinical setting.

3. Traditional Algorithmic Approaches to Gait Event Detection

Prior to deep learning, the use of deterministic algorithms for gait event detection was based on either kinematics (position/velocity/acceleration) or kinetics (force). These techniques constitute what is commonly referred to as the ground truth labels that are employed to train modern neural networks.

3.1 Kinetic Detection (Force Plates)

GRF has been considered to be the very best means of determination of stance phase because direct measurements were done on Ground Reaction Force (GRF). Caderby et al. (2013) had paid attention to identifying the swing heel-off point in the onset of the gait. They could determine the exact change of the center of pressure used as force-plate data so the step starts. Although very precise, force plates are built in the floor, which is a great constraint to the capture volume as it can only capture a small number of steps. This drawback makes them inappropriate when it comes to tracking continuous gait through time so that intermittent deformities can be identified or that changes, as a result of fatigue, can be observed.

3.2 Kinematic Algorithms

Motorcycles In order to eliminate the spatial constraints of force plates, investigators created algorithms through the motion capture markers.

Hreljac and Marshall (2000) suggested an approach whereby the acceleration of the markers on the heel and toes was used. Hypothesis These scientists postulated that HS and TO are represented as separate peaks in the vertical acceleration profile. Their algorithm was seen to be strong in normal walking but was frequently seen to need threshold tuning.

Ghoussayni et al. (2004) compared a straightforward electronic technique whereby the vertical speed of heel and toe was used. Analyzing crossings of zero with velocity profiles and their minima they obtained a high accuracy with the data of the force plates. They however, observed that the performance of the algorithm decreased marginally when the walking speed was slow which usually characterizes patients with musculoskeletal impairments.

O' Connor et al. (2007) presented an algorithm that uses relative velocity between the sacrum and heel. This was new as it used an object proximal (the sacrum), and thus it would be less susceptible to localized foetuses of the foot as opposed to methodologies that used the foot markers.

It was further reduced in the method suggested by Zeni et al. (2008), who suggested the coordinate-based method. They showed that with the use of minimum and maximum horizontal tracking of the heel / toe marker and the sacral marker, they were able to detect gait events. The point of time at which the heel was most anteriorly positioned usually was heel strike and the point of time which was most posterior was toe-off. This technique is computationally cheap and is popular, however, its accuracy may not be repeatable between running and walking as Fellin et al. (2010) indicated, and also may not be accurate in pathological gaits where compromised step length may occur.

Karcnik (2003) concentrated on the use of this motion analysis data in detecting foot-floor contacts with the express purpose of the replacement of force plates. The paper demonstrated that although kinematic algorithms work, they are more like broodstock of the physical phenomenon of contact and there is a certain delay or time lag between the kinematic phenomenon (i.e. reaching maximum extension) and the kinetic one (i.e. force application).

Anusandhanvallari
Vol 2025, No.1
December 2025
ISSN 2229-3388

3.3 Limitations in Pathological Gait

The main mode of failure in these conventional algorithms is the fact that these algorithms assume normal gait morphology. Hsue et al. (2007) stated this among children with cerebral palsy. In toe-walking (equinus), the heel can not touch the ground but if it does, the contact with the ground cannot be distinguished with a heel or mid-stance point on the kinematic profiles. Algorithms that attempt to find a peak velocity at heel strike will not work or give false timing measures in such populations. This non-generalizability gave rise to the transition towards the probabilistic and learning-based methods.

4. The Era of Wearable Sensors

In order to identify musculoskeletal deformities in everyday life, the practice shifted off optical motion capture to wearable sensors. This revolution created the huge volumes of data required in deep learning.

4.1 Accelerometry and IMUs

Yang and Hsu (2010) have presented a detailed overview of motion detectors based on accelerometer. Their categorization of systems depended on the position of the sensor (waist, ankle, foot) and also functionality. They concluded that accelerometers are useful in the measurement of the intensity of physical activity, the specificity of gait events could only be detected accurately when complex signal processing was performed to eliminate gravitational and sensor-related artifacts.

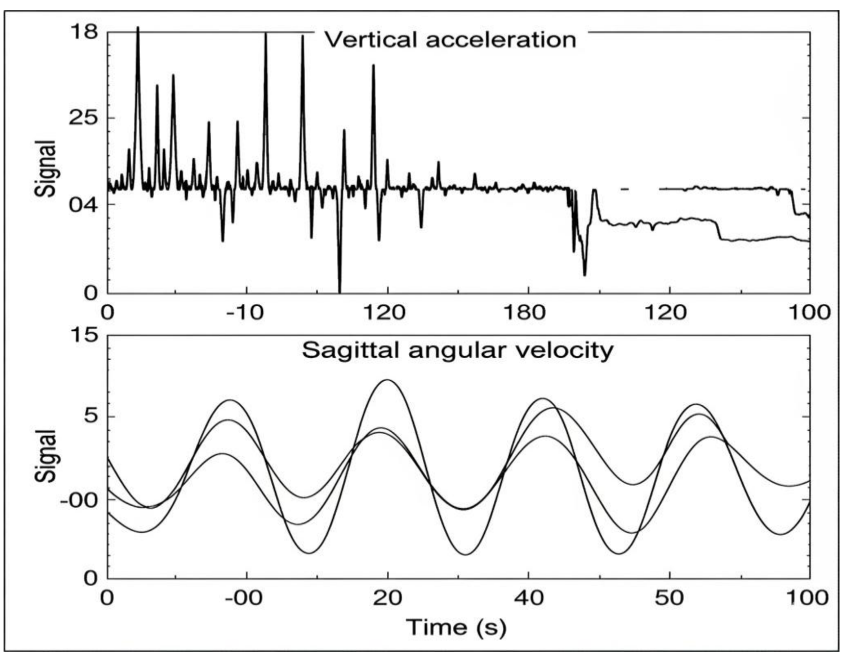

Figure 2: Typical raw signal output from a foot-mounted Inertial Measurement Unit (IMU). The distinct peaks and troughs in the acceleration (top) and angular velocity (bottom) correspond to specific gait events, such as heel strike and toe-off, which serve as inputs for machine learning models.

The article by Appelboom et al. (2014) covered the emergence of the so-called smart wearable body sensors to evaluate patient conditions themselves. They thought that by constantly observing them, weak changes in gait would be noticed which would not have been identified by a 30 minute clinical review. In case of musculoskeletal deformities, it becomes essential; a patient may walk fairly well in the morning but show serious pathological worsening (limp, drag) further in the day period because his/her muscle tiredness.

4.2 Sensor Fusion and Drift Correction

The single sensors are prone to integration drift, whereby minor errors in acceleration value add up to produce huge position errors as the sensor advances. Fourati (2015) dealt with this by suggesting a heterogeneous algorithm of data fusion. Fourati showed that it was possible to reduce drift effects by using a foot-mounted Inertial Measurement Unit (IMU) to measure the pedestrian motion and use this information to perform the complementary filter, which would allow a more accurate way to navigate the environment.

Olsen et al. (2012) also validated this on quadrupedal gait (equine), which used inertial sensors mounted on the limbs and trunk. Although they had an interest in the field of veterinary, the results of the outcomes on human biomechanics were obvious: the location of sensors has a significant impact on the quality of data. Good center of mass information is obtained by trunk mounted sensors, and the best ones are the limb mounted sensors (HS, TO).

Jasiewicz et al. (2006) particularly made comparisons of the linear accelerators and angular velocity transducers (gyroscopes) in able-bodied people and those in Spinal Cord Injury (SCI). Their results were that the gyroscopes gave signals that were less contaminated by the other event-related signals in the SCI population since angular velocity signals of the shank and foot had recognizable characteristics despite a dampening of the acceleration profiles or in under the conditions of chaos caused by the pathology.

5. Machine Learning and Deep Learning Integration

The intricacy of signal patterns at IMUs, particularly in pathological gait renders simple threshold based algorithms. It resulted in the implementation of machine learning classifiers and then deep learning.

5.1 Early Neural Networks and Fuzzy Logic

Conventional learning constructions, known as shallow learning, were used before the mainstreaming of Deep Learning. There was a creation of a real time gait event detector in paraplegic patients using Functional Electrical Stimulation (FES) by Skelly and Chizeck (2001). Their mechanism must have been extremely sensitive to cause stimulation at occurring at the optimal point in the gait cycle. They applied expert knowledge derived fuzzy logic rules, which resulted in a reliable triggering of the paraplegic gait that is extremely abnormal.

Lauer et al. (2005) used the neuro-fuzzy network to identify the gait events in kids with Cerebral Palsy with the help of Electromyography (EMG). This approach compared muscle activation patterns, unlike the kinematic approaches. The non-linear association between the muscles firing with the movement of the limb could be handled by the neuro-fuzzy model. This was a key advance to automatic detection since it associated biological indicators with artificial intelligence to discern gait stages in grossly deformed musculoskeletal systems.

Miller (2009) used a multilayer perceptron (simpler neural network) to make gait event detection. The works of Miller showed that a neural network might learn a particular gait signature of a person, and performed better when compared to a generic group-based algorithm. Nonetheless, these earlier networks were manually designed: the inputs were to be processed (e.g. peak velocity, average variance).

5.2 Hidden Markov Models (HMM)

Mannini et al. (2014) made a step forward introducing Hidden Markov Models to data collected by the use of foot-mounted gyroscopes. HMMs are probabilistic models that are particularly well-posed to time-series data with a state (i.e. swing phase, stance phase) that is not observable yet gives observable signals (gyroscope readings). The method used by Mannini enabled the on-line decoding, i.e. the system was able to identify the gait stage in real-time. This is necessary with assistive devices such as active orthoses which require response to a movement of the user immediately.

5.3 Deep Convolutional Neural Networks (CNNs)

The largest step forward is explained in the writings of Hannink et al. (2017, 2018). Hannink et al. (2017) were interested in the shortcomings of manual feature engineering in their article. They established a Deep Convolutional Neural Network (DCNN) of sensor based gait parameters extraction. The DCNN accepts raw sensor data as input which is unlike the past approaches. The convolutional layers are auto-extractors of features, filters that are capable of learning complicated features like a vibration pattern that a heel strike has, or a curve of a rotational acceleration of a motion with a pathological swing phase. This model was demonstrated to be better in estimating the stride length, width and gait speeds than standard double-integration techniques.

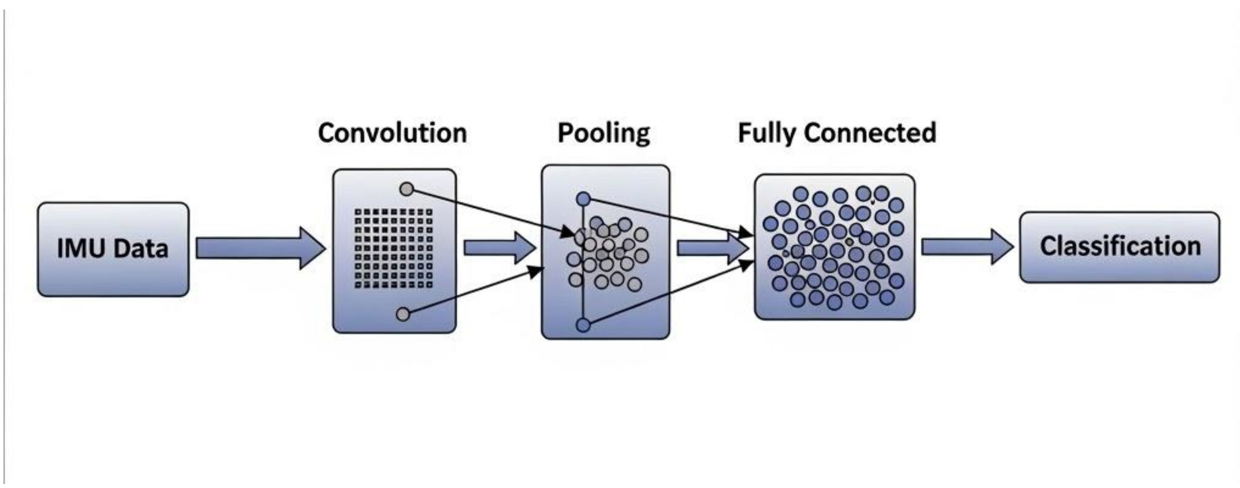

Figure 3: A schematic representation of a Deep Convolutional Neural Network (DCNN) architecture used for gait parameter extraction. The network processes raw sensor inputs through multiple convolutional and pooling layers to automatically learn hierarchical features, outputting spatial parameters such as stride length.

Anusandhanvallari
Vol 2025, No.1
December 2025
ISSN 2229-3388

Hannink et al. have in 2018 extended this to the mobile stride length estimation. Stride length is an essential biomarker of most deformities; e.g. the asymmetry of stride length is a sign of hemiplegia. Their DCNN image model was trained on a big dataset and it showed that with deep learning it was possible to map the non-linear and intricate correlation between the IMU signals and the spatial gait parameters with high accuracy.

The strength of the Deep Learning method, which is emphasized by these studies, is strength. A DCNN, which has been trained using a mixed dataset (both healthy and pathological gaits) produces a generalized representation of human walking. It is based less on particular peaks (which may not exist in deformity) and more on the overall form of the signal waveform.

6. Clinical Applications: Detecting and Monitoring Deformities

With the intersection of biomechanics, wearables, and DL, it is possible to identify particular deformities automatically.

6.1 Cerebral Palsy (CP) and Equinus Deformity

CP is a complicated entity to monitor. Kuo et al. (2009) compared activity monitoring in CP children to portable activity monitors. Their results showed that the number of steps was mostly correct, but the devices were not as successful with irregular gait patterns and reduced speeds of CP. Nevertheless, by combining neuro-fuzzy solution of Lauer et al. (2005) and with the kinematic knowledge of Hsue et al. (2007), it is now possible to train the current deep learning models to identify the signature of toe-walking. At the initial contact, the gyroscope exhibits a certain type of rotation (dorsiflexion) in the healthy walk. This has been substituted in equinus gait by plantarflexion. Using this inverted signal signal, a Deep Learning model can determine a stride to be a pathological one, which is a number of toecap-walking steps vs. heel-strikes steps each day. The measure is invaluable to evaluating the effectiveness of an intervention such as Botox injections or tendon lengthening procedures.

6.2 Spinal Cord Injury (SCI) and Drop Foot

Jasiewicz et al. (2006) proved that angular velocity transducers can be used with SCI patients. SCI frequently causes drop foot in which the affected individual is unable to raise his toes during the swing phase resulting in either a dragging movement or high-stepping compensatory gait. The absence of the swing-phase clearance can be referred to through automatic detection systems based on the HMMs (Mannini et al., 2014), as well as CNNs. The system can notify the clinicians of the worsening of the patient condition or necessity of an Ankle-Foot Orthosis (AFO), by either sensing the dragging event (through the spikes of the accelerator at mid-swing) or the compensatory hiking of the hips (through the trunk IMUs).

6.3 Rehabilitation and Stability

The stability measures addressed by Dingwell et al. (2001) can be also calculated through the deep learning. The system can pick up small variations of variability (which lead to a fall) by providing long sequences of gait cycles into a network (perhaps a Recurrent Neural Network or Long Short-Term Memory model, but CNNs also process time-series). In patients who are recovering after orthopedic surgery, or have an orthopedic deformity, the given "stability score" is an automatic, objective progress report.

7. Discussion: Synthesis and Future Challenges

There is a very clear direction of the literature: the hard, highly precise, yet limited location-wise gait lab environment (Davis, Kadaba) versus an AI analytics-based, wearable one.

7.1 The "Black Box" Problem vs. Clinical Interpretability

A conflict in the discipline is between the illustrativeness of kinematic methods and the opaceness of Deep Learning. We can be sure that the likes of Zeni (2008) algorithm are transparent since once it fails, we can tell that the heel marker did not reach the sacrum threshold. Contrastingly, when a CNN (Hannink et al., 2017) makes a wrong classification of a gait, it is usually challenging to comprehend the reason why. But, this disadvantage is usually outweighed by the performance-level benefits of DL, notably its capability to deal with the noise of the real-world walking (sensor drift, surface discontinuity).

7.2 Data Domain Shift

The findings of Alton (1998) and Fellin (2010) regarding treadmill vs. overground differences remain a critical challenge for DL. If a neural network is trained solely on large datasets of treadmill walking (which are easier to collect), it may fail when applied to free-living overground walking due to differences in kinematic variability. Future research must focus on Transfer Learning, where models pre-trained on treadmill data are fine-tuned with smaller sets of overground data.

7.3 Integration of Heterogeneous Data

Fourati's (2015) work on sensor fusion hints at the future. Truly robust automatic detection of deformities will likely not rely on a single sensor modality. It will fuse kinematic data (IMUs), kinetic estimates (pressure insoles), and perhaps physiological data (EMG, as per Lauer 2005). Deep Learning is uniquely suited for this "multimodal" fusion, capable of learning correlations between muscle activity and limb motion that are too complex for manual mathematical modeling.

8. Conclusion

The automatic detection of musculoskeletal deformities has evolved from a geometric problem solved in gait laboratories to a data science problem solved by neural networks. The literature confirms that while traditional kinematic algorithms (Zeni et al., 2008; Hreljac & Marshall, 2000) established the biomechanical ground truth, they lack the flexibility to handle the high variability of pathological gait in uncontrolled environments.

Wearable sensors (Yang & Hsu, 2010; Appelboom et al., 2014) have democratized data collection, but introduced noise and drift challenges (Fourati, 2015). Deep Learning, specifically Deep Convolutional Neural Networks (Hannink et al., 2017, 2018), has emerged as the most potent solution, capable of extracting robust gait parameters from raw sensor data without manual thresholding.

For patients with Cerebral Palsy, Spinal Cord Injuries, or other deformities, this technology promises a shift from reactive medicine—treating a deformity once it is visually obvious—to proactive monitoring. By automatically detecting subtle biomechanical deviations (Hsue et al., 2007; Jasiewicz et al., 2006) in daily life, AI-driven gait analysis facilitates earlier intervention, personalized rehabilitation, and ultimately, better functional outcomes. The future lies in refining these deep learning models to be interpretable, data-efficient, and robust across the diverse environments in which patients live and move.

References

1. Alton, F., Baldey, L., Caplan, S. and Morrissey, M. (1998) 'A kinematic comparison of overground and treadmill walking', *Clinical Biomechanics*, 13(6), pp. 434–440. doi: 10.1016/S0268-0033(98)00012-6.
2. Appelboom, G. et al. (2014) 'Smart wearable body sensors for patient self-assessment and monitoring', *Archives of Public Health*, 72(1), p. 28. doi: 10.1186/2049-3258-72-28.
3. Caderby, T., Yiou, E., Peyrot, N., Bonazzi, B. and Dalleau, G. (2013) 'Detection of swing heel-off event in gait initiation using force-plate data', *Gait & Posture*, 37(3), pp. 463–466. doi: 10.1016/j.gaitpost.2012.08.011.
4. Davis, R.B. III, Ounpuu, S., Tyburski, D. and Gage, J.R. (1991) 'A gait analysis data collection and reduction technique', *Human Movement Science*, 10(5), pp. 575–587. doi: 10.1016/0167-9457(91)90046-Z.
5. Dingwell, J., Cusumano, J., Cavanagh, P. and Sternad, D. (2001) 'Local dynamic stability versus kinematic variability of continuous overground and treadmill walking', *Journal of Biomechanical Engineering*, 123(1), pp. 27–32. doi: 10.1115/1.1336798.
6. Fellin, R.E., Rose, W.C., Royer, T.D. and Davis, I.S. (2010) 'Comparison of methods for kinematic identification of footstrike and toe-off during overground and treadmill running', *Journal of Science and Medicine in Sport*, 13(6), pp. 646–650. doi: 10.1016/j.jsams.2010.03.006.
7. Fourati, H. (2015) 'Heterogeneous data fusion algorithm for pedestrian navigation via foot-mounted inertial measurement unit and complementary filter', *IEEE Transactions on Instrumentation and Measurement*, 64(1), pp. 221–229. doi: 10.1109/TIM.2014.2335912.
8. Ghoussayni, S., Stevens, C., Durham, S. and Ewins, D. (2004) 'Assessment and validation of a simple automated method for the detection of gait events and intervals', *Gait & Posture*, 20(3), pp. 266–272. doi: 10.1016/j.gaitpost.2003.10.001.
9. Hannink, J. et al. (2017) 'Sensor-based gait parameter extraction with deep convolutional neural networks', *Journal of Biomedical and Health Informatics*, 21(1), pp. 85–93. doi: 10.1109/JBHI.2016.2636456.
10. Hannink, J. et al. (2018) 'Mobile stride length estimation with deep convolutional neural networks', *IEEE Journal of Biomedical and Health Informatics*, 22(2), pp. 354–362. doi: 10.1109/JBHI.2017.2679486.
11. Hreljac, A. and Marshall, R.N. (2000) 'Algorithms to determine event timing during normal walking using kinematic data', *Journal of Biomechanics*, 33(6), pp. 783–786. doi: 10.1016/S0021-9290(00)00014-2.
12. Hsue, B., Miller, F., Su, F., Henley, J. and Church, C. (2007) 'Gait timing event determination using kinematic data for toe-walking children with cerebral palsy', *Journal of Biomechanics*, 40(S2), p. S529. doi: 10.1016/S0021-9290(07)70519-5.

13. Jasiewicz, J.M. et al. (2006) 'Gait event detection using linear accelerometers or angular velocity transducers in able-bodied and spinal-cord injured individuals', *Gait & Posture*, 24(4), pp. 502–509. doi: 10.1016/j.gaitpost.2005.12.017.

14. Kadaba, M.P., Ramakrishnan, H. and Wootten, M. (1990) 'Measurement of lower extremity kinematics during level walking', *Journal of Orthopaedic Research*, 8(3), pp. 383–392. doi: 10.1002/jor.1100080310.

15. Karčnik, T. (2003) 'Using motion analysis data for foot–floor contact detection', *Medical and Biological Engineering and Computing*, 41(5), pp. 509–512. doi: 10.1007/BF02345310.

16. Kuo, Y.L., Culhane, K.M., Thomason, P., Tirosh, O. and Baker, R. (2009) 'Measuring distance walked and step count in children with cerebral palsy: an evaluation of two portable activity monitors', *Gait & Posture*, 29(2), pp. 304–310. doi: 10.1016/j.gaitpost.2008.09.014.

17. Lauer, R.T., Smith, B.T. and Betz, R.R. (2005) 'Application of a neuro-fuzzy network for gait event detection using electromyography in the child with cerebral palsy', *IEEE Transactions on Biomedical Engineering*, 52(9), pp. 1532–1540. doi: 10.1109/TBME.2005.851527.

18. Mannini, A., Genovese, V. and Sabatini, A.M. (2014) 'Online decoding of hidden Markov models for gait event detection using foot-mounted gyroscopes', *IEEE Journal of Biomedical and Health Informatics*, 18(4), pp. 1122–1130. doi: 10.1109/JBHI.2013.2293887.

19. Miller, A. (2009) 'Gait event detection using a multilayer neural network', *Gait & Posture*, 29(4), pp. 542–545. doi: 10.1016/j.gaitpost.2008.12.003.

20. O'Connor, C.M., Thorpe, S.K., O'Malley, M.J. and Vaughan, C.L. (2007) 'Automatic detection of gait events using kinematic data', *Gait & Posture*, 25(3), pp. 469–474. doi: 10.1016/j.gaitpost.2006.05.016.

21. Olsen, E., Haubro Andersen, P. and Pfau, T. (2012) 'Accuracy and precision of equine gait event detection during walking with limb and trunk-mounted inertial sensors', *Sensors*, 12(6), pp. 8145–8156. doi: 10.3390/s120608145.

22. Schache, A.G. et al. (2001) 'A comparison of overground and treadmill running for measuring the three-dimensional kinematics of the lumbo–pelvic–hip complex', *Clinical Biomechanics*, 16(8), pp. 667–680. doi: 10.1016/S0268-0033(01)00061-4.

23. Skelly, M.M. and Chizeck, H.J. (2001) 'Real-time gait event detection for paraplegic FES walking', *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 9(1), pp. 59–68. doi: 10.1109/7333.918277.

24. Yang, C.C. and Hsu, Y.L. (2010) 'A review of accelerometry-based wearable motion detectors for physical activity monitoring', *Sensors*, 10(8), pp. 7772–7788. doi: 10.3390/s100807772.

25. Zeni, J., Richards, J. and Higginson, J. (2008) 'Two simple methods for determining gait events during treadmill and overground walking using kinematic data', *Gait & Posture*, 27(4), pp. 710–714. doi: 10.1016/j.gaitpost.2007.07.007.