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# Gait Estimation and Analysis from Noisy Observations

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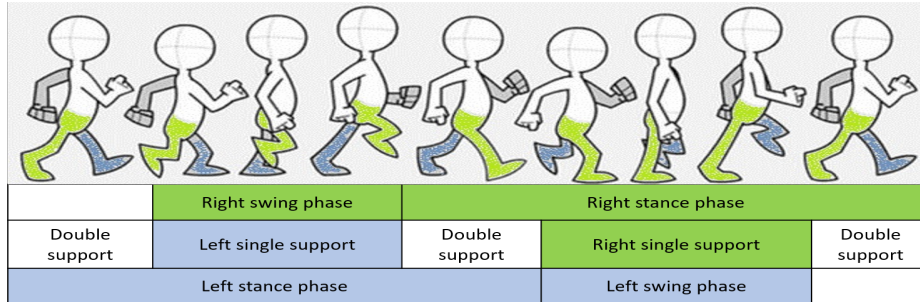
**Abstract.** People’s walking style – gait – can be an indicator of their health as it is affected by pain, illness, weakness, and aging. Gait analysis aims to detect gait variations. It is usually performed by an experienced observer with the help of cameras, sensors, or other devices. Frequent gait analysis, to observe changes over time, is costly and impractical. Here, we first discuss estimating gait movements from predicted 2D joint locations that represent selected body parts from videos. Then, we use a long-short term memory (LSTM) regression model to predict 3D (Vicon) data, which was recorded simultaneously with the videos as ground truth. Feet movements estimated from video correlate highly with the Vicon data, enabling gait analysis by measuring selected spatial gait parameters (step and cadence length, and walk base) from estimated movements. Using inexpensive and reliable cameras to record, estimate and analyse a person’s gait can be helpful; early detection of its changes facilitates early intervention.

**Keywords:** Gait analysis, machine learning, regression, vision data

## 1 Introduction

Gait is the manner or style of walk. Gait analysis evaluates this style of locomotion [1]. While walking, one limb provides body support (stance phase for that leg), while the other leg swings forward (swing phase for that leg) in preparation for stance phase. The combination of stance and swing phases forms the gait cycle as shown in Fig. 1. In normal Walk, a symmetry occurred in the movements of both feet.

A person’s walk can be affected by pain, weakness, aging or injuries. Thus, gait abnormalities can be an indicator of a person’s health. Gait abnormalities can be detected by an experienced physiotherapist who observes the walking style and measures parameters to analyse the gait with the help of different devices. These gait parameters are: 1) Temporal and spatial, such as walking speed and lengths, and can be measured by a stop watch and a measuring tape. Floor sensors, accelerometers and/or wearable sensors can be added for more accurate measurements. 2) Kinematics and kinetics, such as joint movements and angles,



**Fig. 1.** Gait cycle consisting of stride and swing phases for each leg.

and the forces involved to produce these movements. Specific devices are used to measure such parameters, *e.g.* motion capture cameras and force plates. 3) Electromyography, which measures muscle activities during walk. Video recording is used widely in gait analysis for a slow motion analysis of the walk action and the movement of the legs and feet for a detailed assessment.

Human gait and sway has received much attention in computer vision in recent years for human recognition and identification (*e.g.* [2]) and for detecting falls (*e.g.* [3]) using the general shape of the body and/or the movement patterns.

In this paper, we estimate movements of selected body parts (feet, torso) from video using predicted 2D joint locations. The estimated movements are used to derive spatial gait parameters (step and cadence length, walk base). Estimated movements and gait parameters are compared with the ground truth Vicon data and parameters derived from it, respectively. Our long-term goal is to investigate the use of simpler and cheaper video technology as an alternative to costly specialist devices. Related work is presented in the next section, followed by information about the dataset, the proposed method, and the experiments and results.

## 2 Related Work

Early research on measuring and analysing human gait was entirely for medical purposes to distinguish normal gait from a pathological one. Gait analysis was usually performed by an experienced physiotherapist who observed the walking style.

For accurately measuring and characterising human gait, different devices are used to measure body movements, mechanics, and muscle activity. Devices include accelerometers, gyroscopes, or other *wearable* sensors [9, 10], and cameras, force plates, or other *non-wearable* devices. Most of these are expensive and need to be installed and used by a specialist in a laboratory environment.

With the advances in image processing algorithms, analysing gait became an interest for computer vision researchers, *e.g.* to recognise and identify humans from their body movements. Gait is considered to be a biometric characteristic

of an individual. Most computer vision studies on gait use the general shape of the body and/or the moving pattern for abnormal gait detection [5–7], human recognition [8], fall detection [3], and for safety and surveillance purposes.

Human recognition systems using gait have focused on image representation, feature dimensionality, and gait classification [8] to improve recognition. On the other hand, for abnormal gait detection, body silhouettes have been used in [5] to detect and classify the observed walking pattern into normal or abnormal gait based on analysing recorded videos of seven subjects walking in normal and abnormal ways. In [6], the extracted silhouette, with frame-to-frame optical flow and motion metrics based on histogram representations of silhouette-masked flows, was used to determine different styles of walking and detect deviation from usual walking patterns using two separately recorded datasets, one for subjects simulated abnormal gait and the second dataset for professional actors performing pathological gaits.

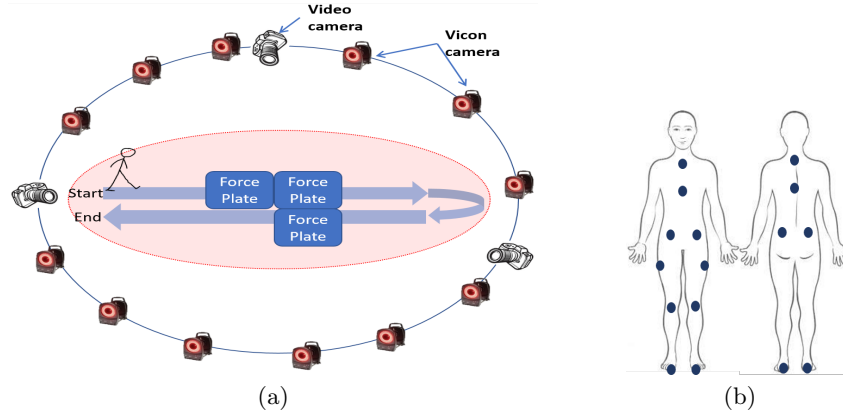
Gait analysis, especially spatial-temporal parameters, is receiving increasing attention in computer vision to provide an inexpensive tool to identify and detect gait abnormalities. Human gait has been classified into normal or abnormal in [7] by calculating some gait spatial-temporal parameters using vision data. The dataset consisted of 30 subjects (15 normally walking, 15 abnormally walking).

For the improvement of all aspects of life, new technologies and approaches are proposed to make the measurement and assessment of health conditions easier, faster, and more reliable. Although some progress has been made in using computer vision techniques for human gait analysis, a need for a technique that measures and analyses human gait in an inexpensive and reliable manner still exists. In this paper, we estimate the human gait from video and explore the utility of automated gait analysis by comparing the results with 3D Vicon data in a newly collected dataset.

### 3 Dataset

After furnishing the proper ethics approvals and research permissions, a dataset that contains walk and balance actions was collected and used for this study. Existing datasets that include gait and balance activities have usually been clinical datasets, collected in health care settings and, hence, were confidential and unavailable to us. Moreover, video cameras or a motion capture system that we need for assessing the accuracy of the modeling were typically not included. While this dataset contains both walking and balance activities, this paper investigates the walking (gait) data only.

Eighteen subjects, twelve males and six females, performed normal walking for about 10m, including making a U-turn after 5m, as well as a balance test on an AMTI force plate. Each subject performed this sequence of activities three times in a row, with a minimal break in between. The activities were recorded by three video cameras: a front view, a side view, and a corner back view. Twelve T-series Vicon cameras were used to capture 3D motion from sixteen markers that were placed on the subject’s body (Fig. 2). As the feet, legs, and trunk



**Fig. 2.** Dataset recording: (a) Lab installation and (b) Vicon marker locations on a subject's body

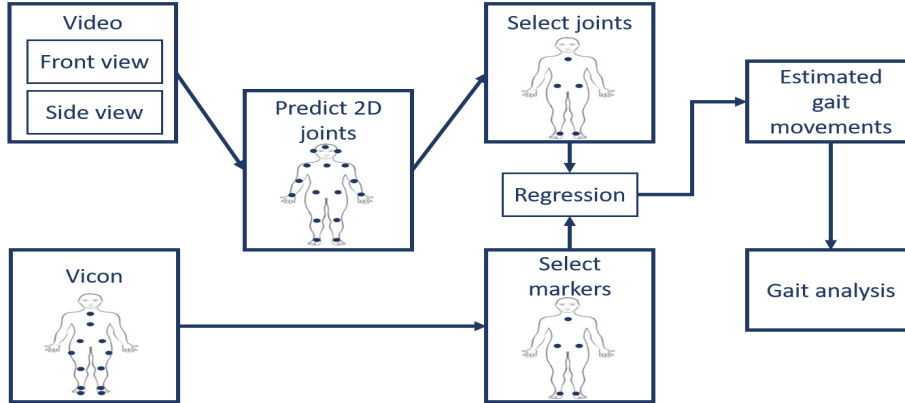
are the major motor reactors in walking, Vicon markers were placed on different joints related to these body parts to capture the body movements during the gait and balance test activities. Captured data from the Vicon cameras and the force plate were systemically synchronised by manually aligning the videos with the heel strike.

## 4 Proposed Method

Our goal is to provide a gait analysis method that is accurate enough to provide an alternative to highly accurate but expensive devices, which also need a special setup and/or need to be worn most of the time. To achieve this goal, both frontal and side views in RGB video cameras are considered. Some parameters, such as walking base and sway, are more obvious from the frontal view while others, such as step and cadence length, are easier to measure from the side view. To determine the accuracy of the calculated gait parameters from videos, Vicon data are used as an accurately captured ground truth for body movements. First, an existing method is used on video frames to estimate the body joint locations. Second, joints of the limb related to the walking action are selected from both video and Vicon. Feet and legs represent the walking activity, whilst upper body movements reflect the body sway when walking or standing (see Fig. 3). Next, we will describe the methods for pre-processing, gait estimation and gait analysis.

### 4.1 Pre-processing

To prepare the variety of data, produced by the Vicon system and video cameras, for gait estimation and analysis, the following steps have been taken.

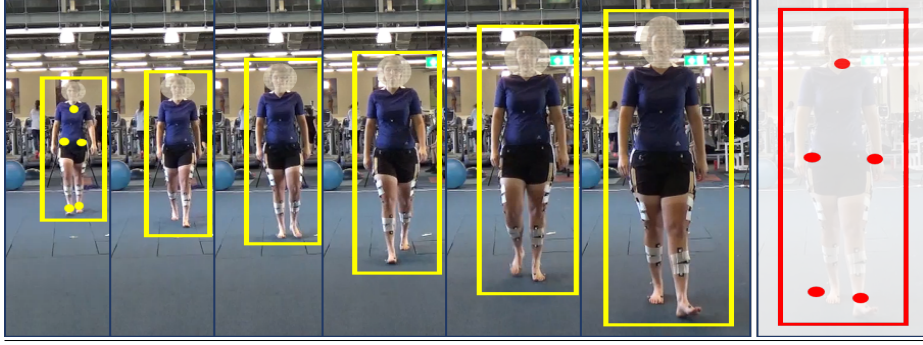


**Fig. 3.** Proposed method: Movements of selected body joint locations from video are regressed with movements from corresponding Vicon markers in order to estimate body part movements and use them in gait analysis. Note that while the Vicon and real life distances are in millimetres, the respective image metric uses pixels. The LSTM regression method is used to estimate joint movement measurements in millimetres for the gait parameter calculations.

**Joint Extraction** The DeepPose method [4] that estimates human pose is applied to extract 2D joint locations of 18 different body parts. 2D joints related to feet, hips, and upper body (torso) are selected for subsequent use in gait estimation and analysis. In the DeepPose method, a generic convolutional deep neural network (DNN) is learned. Using a cascade of DNN-based pose predictors allows for increased precision of joint localisation. Starting with an initial pose estimation, based on the full image, DNN-based regressors are learned to refine the joint predictions by using higher resolution sub-images. The method is used on both side and frontal views.

**Joint Normalisation – Frontal View** Although the extracted joints from the frontal view are clear and represent the body movements over the frames, the movements decay when being too far from the camera. To avoid this distortion, predicted joint locations are normalised to the biggest bounding box that surrounds the body over all video frames (Fig. 4).

**Data Re-sampling** The video and Vicon data are recorded at different frame rates. The video frame rate is 25Hz, while the Vicon system captures the markers' movements at 100Hz. The higher Vicon sampling rate results in a noisy signal. Since the signal of interest (markers' movements) is characterised by low frequencies, the well-known Butterworth filter [11] is applied as a low-pass filter on the Vicon data. It cuts off the high frequencies in order to reduce the noise and make the data better suited for gait analysis through regression with an aim to learn the pattern of movements.



**Fig. 4.** Predicted 2D joints are normalised to the biggest bounding box surrounding the body over the video frames

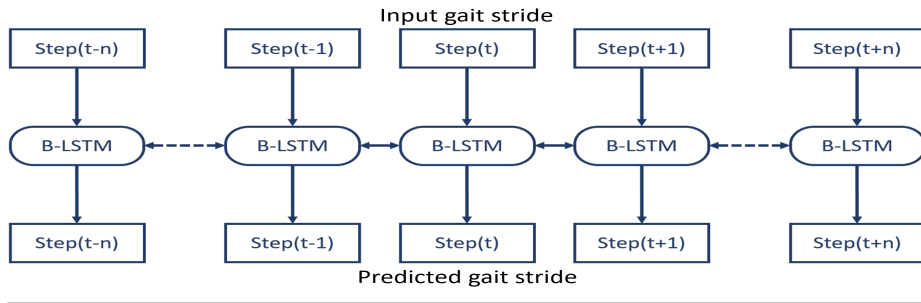
The output of the pre-processing steps are signals that represent the selected joints movements over the video frames and the movements from the corresponding Vicon markers over time. In this paper, we work on the feet markers to calculate the gait parameters, namely step and stride length and walk base.

## 4.2 Gait Estimation and Analysis

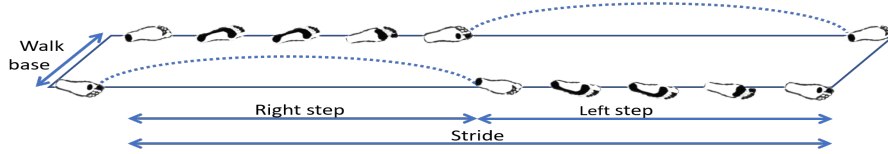
The proposed method for gait estimation (Fig. 4.2) is based on regression. To predict the gait signal in the scale of the Vicon data space, two bi-directional long-short term memory (LSTM) units are used. The output signal at each time  $t$  is estimated by:

$$y(t) = \sigma(\overleftarrow{h}_t, \overrightarrow{h}_t) \quad (1)$$

where,  $\sigma$  is the non-linear activation function of the concatenation or averaging of the forward passing,  $\overleftarrow{h}_t$ , from  $t - n$  to  $t - 1$  and the backward passing,  $\overrightarrow{h}_t$ , from  $t - 1$  to  $t - n$ , where  $n$  is the history size of LSTM unit [12].



**Fig. 5.** The proposed LSTM model



**Fig. 6.** Gait parameters considered in this study: stride and step length, and walk base.

More precisely, the prediction task considers the relationships between the Vicon data and the video signals. The LSTM model is designed based on a many-to-many structure, where the input and the output are of the same size. The sequential connection in its middle layer shows the process of encoding the temporal relationships between the subsequent frames. The input of the model is the signal of one view for a typical joint of the detected pose, which is passed to the two bi-directional LSTM units as an input. Then, the output is passed to a fully connected layer to predict the final output signal.

To analyse gait, we consider the following three spatial parameters (Fig. 6): *stride length*, *step length*, and *walk base*. The stride length is the distance between successive points of heel strike of the same foot. In normal gait, the stride length is twice the step length, which is the distance between corresponding successive points of heel strike of the right and left foot. The walk base is the perpendicular distance between the two lines that pass through the heel strike points, respectively, for the two feet.

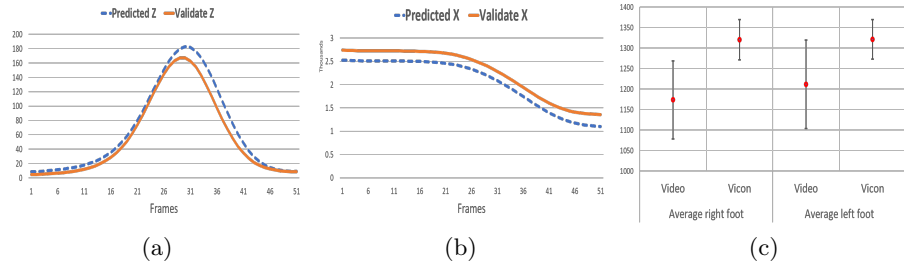
## 5 Experiments and Results

In this section, we present our experiment for applying the proposed method on the walking part of the dataset. First, we estimate feet movements from video and measure the selected spatial gait parameters from these movements. Secondly, we compare both estimated movements and measured parameters with data from the Vicon markers and the gait parameters derived from them. Vicon data is considered as an accurate reference for the collected data as the ground truth or gold standard in this study.

### 5.1 Gait Estimation from Video

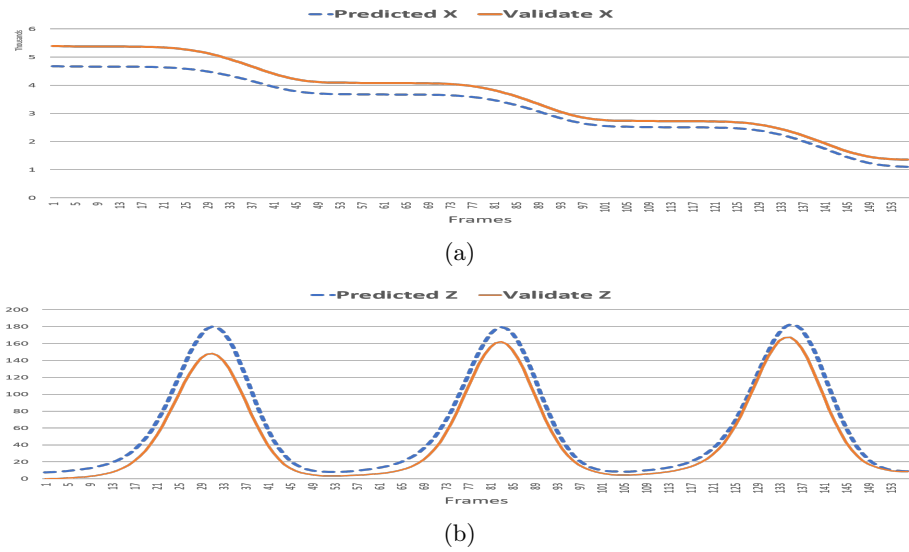
Synchronised video and Vicon data have been cut into single strides (from heel strike to next heel strike for a single foot) as a learning unit to be fed into the proposed LSTM network. An example of estimated gait movements for one stride using the proposed regression method and the corresponding ground truth is shown in Fig. 7. The predicted feet movements in the  $X$ -direction (forward) and  $Y$ -direction (heel contact and off) are correlated with the corresponding Vicon movements with an average of 90% and 95%, respectively, over all subjects as shown in Fig. 7 (c). Movements in the  $X$ -direction are estimated from the side view where the subject crosses the scene, which contains some background



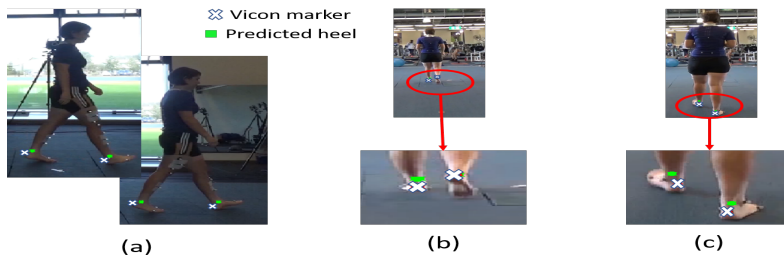


**Fig. 7.** Example of a predicted foot stride compared to Vicon data for (a) vertical movements, (b) forward movements over frames, and (c) the average strides from the estimated joints movement from video and Vicon for booth feet with 95% confidence interval.

objects (*e.g.* a camera tripod) that can lead to the 2D prediction drifting to them, which produces outlier movements in the signal, thus affecting the predicted gait movements. The smaller correlation in the *X*-direction is explained by errors multiplying from the movement extraction phase. Relying on the high correlation of estimated movements with the Vicon data, vision-based data can be used to measure and analyse human gait. Results for a sequence of strides for one foot are shown in Fig. 8.



**Fig. 8.** Example of predicted and ground truth movements in sequence of strides.



**Fig. 9.** Example of a predicted foot joints(square) and Vicon markers(x). (a) side view, (b) good estimated joints, and (c) bad estimated joints for heels.

## 5.2 Spatial Parameter Measurements

As working with 2D joints presentation, stride and step lengths are measured from predicted feet movements in the side view, while step base is measured from predicted feet movements in the frontal view.

The stride length calculated from estimated feet movements shows an average of 1.17m for the right foot with a mean square error (MSE) of 0.036m compared to the Vicon measurements (1.30m) and an average of 1.12m for the left foot with an MSE of 0.044m to the Vicon measurements (1.30m)(Table 1). The step length derived from estimated feet movements shows an average of 0.585m and 0.563m for the right and left foot, respectively, while the average step length for both right and left foot from the Vicon data is 0.65m.

Although the gait parameters measured from predicted feet movements from video and the Vicon markers are close, the slight difference can be traced back to how accurate the extracted 2D feet joints represent the actual feet movements. In the Vicon data the heel strike is well defined because of the marker that is placed on the heel, while the video extracted 2D joint represents the whole foot not only the heel as shown in Fig 9 (a).

The walk base measurements show an average of 4.9cm for the predicted gait movements from video compared to an average of 6cm for the Vicon data. Walk base is relatively small. The slight differences between estimated joints from video and Vicon markers (Fig. 9 (b) and (c)) explain the difference in the walk base measurements.

**Table 1.** Performance evaluation (Mean and MSE measures) for the stride and step predictions for the right and left foot on the test and validation data

		Stride (metre)		Step (metre)	
		Mean	MSE	Mean	MSE
Right	Test	1.17	0.036	0.585	0.040
	Validation	1.30		0.650	
Left	Test	1.12	0.044	0.563	0.047
	Validation	1.30		0.650	

## 6 Conclusions and Future Work

Experiments in this study demonstrate the possibility to analyse gait from estimated gait movements from video – the approach is 90% correlated to the ground truth Vicon data. However, the frame-to-frame human pose estimation generates some errors in the predicted joint locations, which affects the output signals that represent gait movements, and thus also the derived parameters. Our work could be extended by utilising a 3D construction method to analyse gait from monocular view, and including more parameters for gait analysis from video, such as foot and hip angles for more precise gait analysis.

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