Fall Prediction by Analysing Gait and Postural Sway from Videos

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Abstract— **Detecting increases in the likelihood of a fall well before it actually happens will positively affect lives of the elderly. While the main causes of falling are related to postural sway and walking, determining abnormalities in one of these activities or both of them would be informative to predict the fall probability. A need exists for a portable gait and postural sway analysis system that can provide individuals with real-time information about changes and the quality of gait in the real world, not just in a laboratory. This research project aims to build a system that finds the correlation between vision extracted features and force plate data to determine a general gait and body sway pattern. Then, this information is used to assess a difference to normative age and gender relevant patterns as well as any changes over time. This could provide a core indicator of broader health and function in ageing and disease.**

I. Research Vision

Maintaining a high standard of life for the elderly enables them to live their lives with minimum fear of sudden accidents. Falling is one of the most important problems that affect elderly lives. It causes injuries that may be deadly or decrease the functional ability and the quality of life. Predicting falls before they happen makes a critical difference, enabling optimal self-care for elderly adults.

This work aims to develop an application for self monitoring of an individuals based on vision and accelerometer data. Capturing changes in the movement patterns as persons age enables them to intervene if they detect deterioration in movement performance and seek help if needed before a serious fall happens. The research is innovative in that there is no current method of evaluating change in movement performance in walking that can be applied at the individual level that references normative population data. Current assessment of sway, in particular the lateral sway, which is particularly relevant to falls, relies on the use of force platforms. While these have become less expensive in recent years, it is unlikely that these will be omnipresent in homes any time soon.

Our methodology is to build an algorithm to link vision data and force plate data together and to explore the correlation between them. A focus of this algorithm will be on measuring the changes in the lateral sway while standing and walking and quantifying these changes.

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Postural sway is the movement of the body's centre of pressure (CoP) to maintain body balance [1]. A certain amount of sway is essential and inevitable due to small perturbations within the body, such as shifting body weight from one foot to the other, or from external triggers such as visual distortions or floor translations.

During the *process of ageing*, people's postural sway changes and different strategies are used to keep the body balanced. As a result of such changes, the *likelihood of falling* increases as people age.

Measuring body sway while standing can be done by performing one of the balance tests, such as Balance Error Score System (BESS) [2], on the force plate. A force plate captures the body's CoP with high accuracy that reflects the body sway. Different metrics have been identified to measure postural sway to understand the body movements, such as *sway area*, *speed*, *frequency*, and *total path length* [3]. A clinical study of these and other metrics related to the human gait has been initiated in order to analyse human body movements during standing and walking for the purpose of determining the *normal patterns* for these movements and defining any *abnormality* from these patterns when present.

With the evolution in computational imaging and image processing algorithms, studying and analysing human movements has seen much interest from computer vision researchers in recent years. In the literature, the dominating areas of interest are recognising and identifying a person from the walking style and detecting falls.

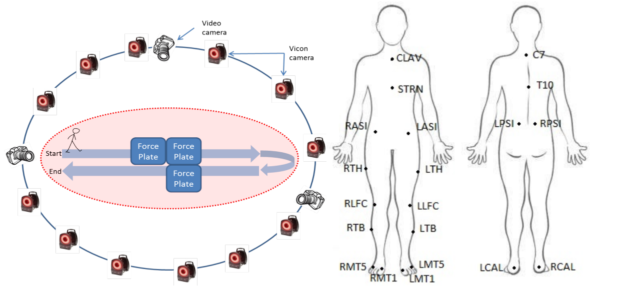
Our work extends this body of knowledge on computer vision systems for analysing gait and postural sway over time in order to detect the abnormal patterns of such movements and predict the increased likelihood of a fall in order to prevent it by winning time to intervene. Specifically, this paper deals with the modelling of the lateral postural sway part and shows that the force plate can be reliably replaced by an inexpensive and mobile video camera to estimate the lateral sway in the context of a balance test.

II. Work Summary

This section summarizes the work that has been done to this end in the main parts of the project: the dataset, postural sway estimation, and gait analysis.

A. Dataset

The dataset is considered as the first contribution in this work. After furnishing the proper ethics approvals and research permissions, a confidential clinical dataset was collected and used for this study. Existing clinical datasets that



(a) (b)

Fig. 1: (a) Recording set up, (b) Vicon markers placed on the human body and their labels.

include gait and postural sway activities and use force plates for measuring the sway have usually been collected in health care settings and, hence, were confidential and unavailable to us. Moreover, video cameras or a motion capture system that we need to assess the accuracy of the modelling were typically not included. On the other hand, computer vision datasets usually do not include postural sway information that we also need. When the dataset contains gait information, it was for tasks such as person tracking, action recognition, or human recognition/identification.

1) Ground Truth Dataset: The ground truth of this study is done by establishing a 3-way correlation between the clinical gold standard (force plate), a highly accurate multi-camera 3D video tracking system (Vicon) and a standard RGB video camera.

Eighteen subjects, males and females, performed normal walking for about 10m, including making a U-turn, as well as the three stances of the BESS test on an AMTI force plates. 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 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. 1).

The measurable object from the videos is the movement of the body parts. As the feet, legs, and trunk are the major motor reactors in maintaining body balance, Vicon markers were placed on different joints related to these body parts to capture the body movements during the gait and balance test activities. There are markers on similar places on the front and the back of the body and they show highly correlated movement patterns. This is important to know for future developments, as it allows the body to be observed from either the front or back with similar results. These markers are *CLAV* (on the clavicle), *C7* (7th Cervical Vertebrae), *STRN* (on the Sternum), *T10* (10th Thoracic Vertebrae), *RASI* (right anterior superior iliac spine), *RPSI* (right posterior superior iliac spine), *LASI* (left anterior superior iliac spine), and *LPSI* (left posterior superior iliac spine). Marker selection for the regression model is based on the average correlation values between extracted medial-lateral sway from the force plate and the tracked labelled joints over all video frames of a sequence.

2) Normative Dataset: This part of the dataset will be collected on three phases separated by three months. Thirty elder people are asked to walk for about 10 metres crossing on the force plate and do the BESS test on the force plate while two video cameras are recording. The Vicon system is excluded from this part of the dataset. Labels are placed on the participants body on points that corresponding to the Vicon markers on torso and legs.

B. Postural Sway Estimation

Postural sway estimation while standing is the second contribution in this work. Starting with a video sequence as input, followed by feature processing, regression was used to build a model to estimate the lateral postural sway (Fig. 2). Put differently, the feature processing step prepared the input video sequences to extract relevant information reflecting the medial-lateral sway – the horizontal right-to-left movements – from which a computational model can be built. Using two non-linear regression methods, namely Gaussian Process Regression (GPR) [4] and Recurrent Neural Network (RNN) [5], [6], [7], to model the postural sway from the preprocessed features by linking them to the data from the force plate. The 3D motion capture data served as an additional way to assess the accuracy of the model.

1) Sway Metrics: Postural sway is usually determined by measuring the movements of the body's CoP captured by the force plate. The area enclosed by the movements of the CoP in the X-Y plane is known as the sway area, which is used as a basic measurement for the postural sway [3]. Total path length, sway speed and frequency are other parameters that are commonly used to describe the amount of postural sway from force plate data. In addition to that computing the sway area using an input from monocular camera is quite difficult, the medial-lateral sway is the body movement that we are interested in, as it is the main predictor for an increased likelihood of a fall. These lateral movements reflect the body balance even while standing.

We devised 1D equivalents to these 2D metrics that can be used to measure, analyse and compare the medial-lateral sway. *Sway signal shape* represents the general pattern of

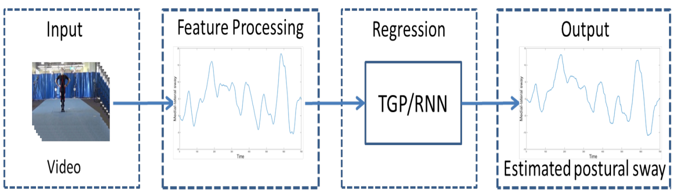


Fig. 2: Proposed methodology: (from left to right) Beginning with the video frames with annotated joint locations in the first frame, these points are tracked over the frames to extract medial-lateral sway, which is passed to the regression model (i.e. Gaussian process regression or recurrent neural network) to estimate the centre of pressure movements, originally measured by the force plate.

medial-lateral sway over a period of time. Then, we use the mean absolute error (MAE) to measure how far the estimated sway is from the corresponding ground truth force plate signal. The correlation between estimated and ground truth signals is also calculated to assess the extent the signals are correlated. *Maximum sway* range and *sway frequency within threshold* are further proposed to analyse the postural sway based on the body medial-lateral sway.

Sway Signal Shape: The similarity in shapes between medial-lateral sway in ground truth from the force plate and the predicted medial-lateral sway from video can be used to confirm that the predicted signal is approaching the ground truth signal. Mean absolute error (MAE) and correlation values are used to quantify this similarity.

Maximum Sway: If one direction of the medial-lateral sway is noted as d, the maximum sway can be determined by the difference between the farthest reached points in both directions d and $-d$. (In this study, this refers to the left-right movements of the body.)

Sway Frequency: Within the specified ranges, a sway frequency represents the number of times the direction of the body's medial-lateral sway changes within one of these ranges in a given time period. In our experiments, the ranges defined in Fig. 3 are used. Bigger maximum sway and high sway frequencies close to the maximum sway range (*red* in Fig. 3) reflect a person's instability and indicate a higher possibility to fall.

2) Sway Estimation from a Single Joint: Estimating postural sway started by using single joint (using more than one joint remains as an extension). The labeled joint that is corresponding to the STRN Vicon marker is used to estimate the postural sway as its movements are highly correlated to the force plate signals compared to other labels.

Using the regression methods TGPR and RNN, we build subject independent models that can predict the medial-lateral sway from tracking the selected joint. This joint is labelled in the first frame of the video and corresponds to the STRN vicon marker. The experiments show the ability to estimate medial-lateral sway from a video sequence at a sufficiently high level of accuracy when compared to the clinical gold standard (force plate). Examples of estimated medial-lateral sway from the tracked STRN joint in the video sequences using TGPR and RNN regression methods are shown in Fig. 4 for the three stances in the BESS balance test. The predicted medial-lateral sway using TGPR is smoothed out, which is a main characteristic of the Gaussian process regression algorithms. Consequently, TGPR is not as good in predicting sudden moves. On the other hand, as shown in the Fig. 4, RNN is better in predicting sudden moves, which are represented by the high peaks in the graphs. Sudden moves occur more frequently in the single leg and tandem stances where maintaining the balance becomes more difficult than in the double leg stance.

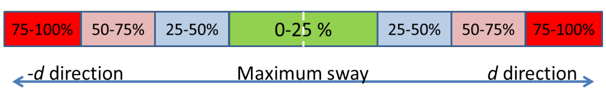
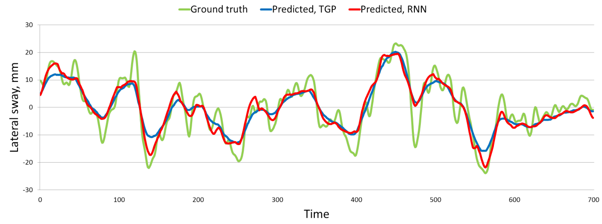


Fig. 3: Visualisation of sway ranges. The more frequent medial-lateral sway values in ranges that are close to the maximum sway, the higher the likelihood of a future fall occurring.



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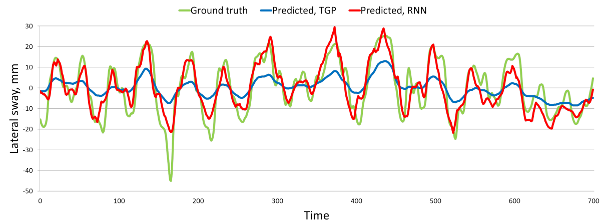

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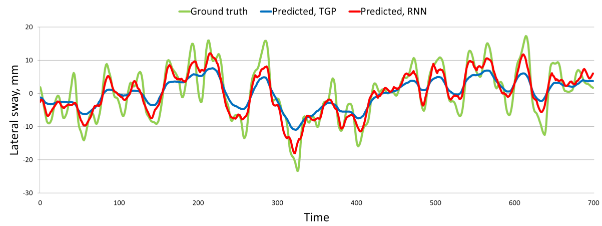
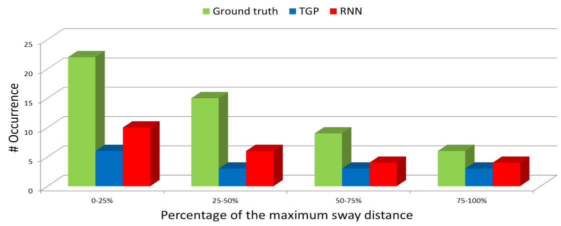


(c)

Fig. 4: Examples of the predicted medial-lateral sway from a tracked joint in the video sequences that corresponds to the STRN Vicon marker in the BESS stances: (a) Double stance, (b) Single leg stance, and (c) Tandem stance. Results are presented as histograms where the bins correspond to the quartiles of the maximum sway range.

The sway ranges, shown in Fig. 3 as quartiles of the maximum sway of each subject, are used to calculate the sway frequencies in the predicted medial-lateral sway and compared to the sway frequencies calculated from the ground truth in the same ranges. Examples for sway frequencies are shown in Fig. 5. In the double stance, most of the medial-lateral sway occurred within the ranges that are close to the mid-point where the balance is more maintainable in this stance. Because of the smoothness in TGPR predictions, changes in the direction of the body sway are imperceptible enough to be counted as a sway change. Single leg and tandem stances have more moves to count within the ranges that are closer to the maximum sway. The RNN method more accurately approaches the sway frequencies of the ground truth in these stances (see Fig. 5(b and c)).



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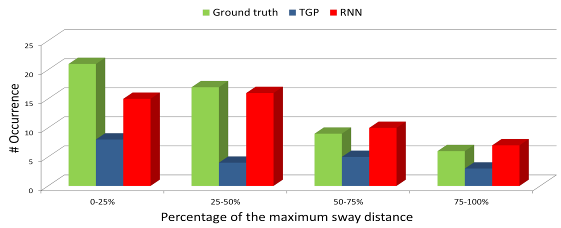

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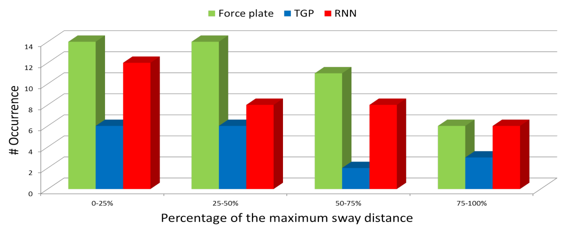

(c)

Fig. 5: Example of sway frequencies that are counted within specified ranges related to the maximum sway for the ground truth signal and predicted signals using TGP and RNN in (a) Double leg stance, (b) Single leg stance, and (c) Tandem stance.

C. Gait measurement and analysis

Many parameters have been identified to measure and analyse human gait [8], [9]. Some of these parameters, such as step base and step length, are changed while ageing to control the body balance while walking. In this work, we try to build a pattern for normal gait within an age group and a pattern of normal changes for an individual over time within this group.

III. Future Plans and Challenges

Medial-lateral sway is an important indication of the human postural sway. Bigger medial-lateral sway indicates poor balance maintaining, which increases the likelihood of a fall in the future. In the current clinical practice, force plates are the gold standard to measure the postural sway. However, they are clinical environment equipment that require special installation, are expensive and are not easily moved.

In this study, the goal is to investigate approaches to predict the medial-lateral sway from tracked joints in RGB video sequences, which would open up the opportunity to use everyday video technology in the assessment of postural sway. To this end, a new dataset was recorded using a force plate as ground truth, RGB video cameras and a Vicon 3D motion capture system to establish a model that accurately predicts lateral sway parameters from simple RGB video input. TGP and RNN were investigated for building a regression model for sway prediction. The RNN based method showed better prediction performance for the medial-lateral sway than TGPR, especially in the tandem and single leg stances, where sudden movements occur more frequently.

The future plan for estimating the postural sway from vision data will focus on: 1) Using a body part detector for the initialisation instead of manually labelling the body parts in the first video frame. 2) As the sway movements are small, we hypothesise that amplifying these movements would improve the extracted features from the video sequences to estimate the body postural sway. 3) Generalising the current framework for different stances and different types of postural sway.

The main future goal for this work is to predict an accurate warnings for the increased fall risk based on the gait and postural sway of the subjects over longer periods of time.

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