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Assessing the Feasibility of Classifying Toe-Walking Severity in Children with Cerebral Palsy Using a Sensorized Shoe

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Abstract— **The clinical management of children with cerebral palsy (CP) relies on monitoring changes in the severity of gait abnormalities and on planning appropriate clinical interventions. Currently available technology does not make it possible to perform clinical gait evaluations as often as it would be desirable from a clinical standpoint. The use of wearable technology (e.g. a sensorized shoe) could provide an effective means to monitor changes in the severity of gait abnormalities in children with CP. In this paper, we studied a group of children with CP who showed an equinus (i.e. toe-walking) gait pattern, a gait abnormality often observed in children with CP. The aim of the study was to determine the feasibility of relying upon a sensorized shoe to assess changes in the severity of toe-walking. We demonstrated that it is possible to use features extracted from the center of pressure trajectory and ankle kinematics to predict the severity of toe-walking. Our results motivate the development and clinical testing of a sensorized shoe to assess changes in gait patterns that accompany the development, and the response to clinical interventions, of children with CP.**

I. Introduction

Cerebral palsy (CP) describes a group of permanent disorders of the development of movement and posture, that are attributed to non-progressive disturbances that occurred in the developing fetal or infant brain [1]. In the United States, approximately 10,000 infants and babies are diagnosed with CP every year [2]. CP can be caused by a metabolic problem before birth, by a lack of oxygen reaching the fetus during delivery, by an infection or stroke either before or after birth or by other medical complications during childhood [3]. These events lead to impaired balance, gait abnormalities, poor coordination, abnormal reflexes, and a delay in developing motor skills. Physical therapy, orthoses, botulinum toxin injections and surgery, are tools available to clinicians to help control and improve gait in children with CP. To determine which intervention is most appropriate to restore mobility, clinical evaluations are carried out to assess impairments and functional limitations and gait analyses are performed using specialized equipment [4]. Frequent assessments are necessary as the child develops and to evaluate the child's response to interventions over time.

Current approaches to gait analysis rely upon (1) camera-based systems, which provide clinicians with detailed information on joints kinematics and kinetics, and (2) observational tools that are based on the qualitative assessment (via visual inspection) of the patient's patterns of movement. These approaches are not suitable for performing assessments of the severity of gait abnormalities in children with CP as often as it would be desirable. This is due to the limited access to these assessment procedures. A wearable system such as a sensorized shoe would offer a means of monitoring children in the field. This would enable the assessment of outcomes to interventions and facilitate treatment planning, thus improving the quality of care for children with CP.

In this paper, we present work aimed at determining the feasibility of developing a sensorized shoe for field assessments of the severity of toe-walking in children with CP. Our hypothesis is that the severity of gait abnormalities associated with toe-walking that is captured via observational gait analysis can be assessed via analysis of the trajectory of the center of pressure (CoP) and the kinematics of the ankle. These are measures that could be gathered using a sensorized shoe. Our goal is to develop methods that perform comparably to a clinical scale for observational gait analysis. Using the proposed approach we hope to offer a means of performing reliable longitudinal field assessments in children with CP.

II. Methods

A. Dataset description

The dataset for this study comprised recordings from children with CP who underwent a gait evaluation at Spaulding Rehabilitation Hospital. It included data from 30 children with CP (age 9.2 ± 2.9 years) who showed an equinus gait pattern, i.e. a pattern in which the foot is

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predominantly plantarflexed during the gait cycle. Children affected by this kind of gait deviation are referred as "toe-walkers". The total number of trials included in the study was 239. The number of trials per subject was fairly even.

Gait trials were performed on a level walkway in the Motion Analysis Laboratory. Reflective markers were attached to pelvis and legs of each child using a standardized setup for the study of lower limb biomechanics. Kinematic curves were reconstructed from trajectories of the markers recorded by an 8-camera motion capture system (Vicon 512, Vicon Peak, Oxford, UK) using a standard biomechanical model (Vicon Plug-in-Gait). Center of pressure trajectories were estimated using two staggered force platforms (AMTI, Watertown, MA) embedded in the walkway.

B. Data processing

Kinematic data (sampled at 120Hz) were extracted for each stride (from foot contact to foot contact of the same foot) and then resampled so as to have 101 samples for each stride. Data from the force platforms were filtered with a Type II, 4^{th} order Chebyshev filter with cut-off frequency of 20 Hz and then segmented and resampled as per the kinematic data. The CoP trajectories were normalized by the foot length so as to allow comparison of features derived from CoP trajectories from children with different foot sizes.

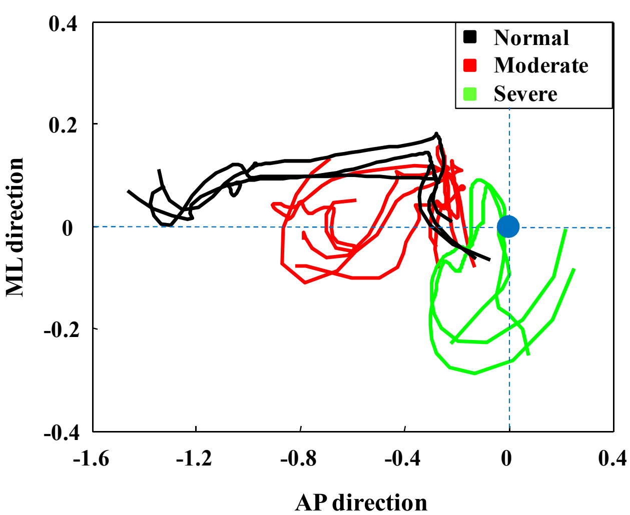

Fig 1. CoP trajectories for 3 children showing different severity levels of toe-walking. The blue circle represents the position of the toe marker (II Metatarsal Head) at the end of the stance phase. See text for details.

C. Feature extraction

Examples of the CoP trajectories, extracted from trials of children affected by different severities of toe-walking, are shown in Figure 1. The trajectories are clearly different and are characterized by a decreased AP range of movement with increased severity of toe-walking. Other differences are also evident such as how well the trajectory of the CoP can be approximated via linear regression. Similar considerations were made in relation to ankle kinematics. Based on visual observation of the CoP trajectories and ankle kinematics, we selected a set of features that we expected to capture the differences between datasets recorded from children with different levels of severity of toe-walking. The feature-set is summarized in Table 1.

TABLE 1
FEATURES EXTRACTED FROM CoP AND ANKLE KINEMATICS

FEATURES	DESCRIPTION
1. AP Displacement	Range of displacement of the CoP in the antero-posterior direction
2. ML Displacement	Range of displacement of the CoP in the medio-lateral direction
3. AP/ML ratio	Ratio between the AP and ML displacements
4. Path length/AP Disp.	Ratio between the CoP path length and its range in AP direction
5. AP mean value	Mean value of the CoP in the antero-posterior direction
6. ML mean value	Mean value of the CoP in the medio-lateral direction
7. AP mean (early stance)	Mean value of the CoP in antero-posterior direction in 0%-10% gait cycle
8. ML mean (early stance)	Mean value of the CoP in medio-lateral direction in 0%-10% gait cycle
9. AP mean (mid stance)	Mean value of the CoP in antero-posterior direction in 10%-30% gait cycle
10. ML mean (mid stance)	Mean value of the CoP in medio-lateral direction in 10%-30% gait cycle
11. AP mean (late stance)	Mean value of the CoP in antero-posterior direction in 30%-50% gait cycle
12. ML mean (late stance)	Mean value of the CoP in medio-lateral direction in 30%-50%gait cycle
13. Distance	Distance between contact point and foot-off point
14. Entropy	Signal entropy
15. Max dorsiflexion (stance)	Maximum dorsiflexion angle of the ankle during the stance phase
16. Max dorsiflexion (swing)	Maximum dorsiflexion angle of the ankle during the swing phase
17. Dorsiflexion at foot contact	Dorsiflexion angle of the ankle at instant of foot contact
18. Dorsiflexion at foot off	Dorsiflexion angle of the ankle at the instant of foot off
19. Ankle dorsiflexion range	Range of dorsiflexion of the ankle through the whole gait cycle
20. Mean rotation	Mean value of the foot progression angle through the stance phase
21. Max rotation	Maximum value of the foot progression angle through the stance phase

D. Edinburgh Visual Scale

We used the Edinburgh Visual Scale developed by Read et al. [5] to assess the severity of toe walking. This scale has been proposed and validated for the assessment of gait deviations in children with CP. The scale consists of a tabulated scoring system, formulated so as to record 17 observations for each lower limb; the items represent key features of pathological gait in patients with CP. The observations are made at six different anatomical levels (foot, ankle, knee, hip, pelvis and trunk) in the sagittal, coronal and transverse planes. For each observation a score from 0-2 is assigned based on the level of severity. If the observation is normal it is scored as 0, moderate deviations are scored as 1 and severe deviations are scored as 2. The scores were assigned by an expert clinician after observing the videos of the children walking while they were undergoing clinical gait analysis. We decided to base our analysis on the first seven observations of the scale, as they are focused on deviations of the ankle-foot complex, which is of primary interest in toe-walking (see Table 2).

TABLE 2
OBSERVATIONS 1-7 OF THE EDINBURGH VISUAL SCALE

Observation	Description
1	Foot contact (heel, flat foot, toe)
2	Heel lift (normal, early, no heel contact)
3	Maximum ankle dorsiflexion in stance
4	Hindfoot varus/valgus
5	Foot rotation (internal/external)
6	Clearance in swing
7	Maximum ankle dorsiflexion in swing

E. Classification

We chose a Random Forest (RF) classifier to predict the scores of the 7 observations of the Edinburgh Visual Scale based on kinematic and CoP data. RF is an ensemble of several weak, weakly-correlated decision trees and the classification output is obtained by voting between individual trees [6]. Classification error was estimated by using 10-fold cross validation.

The two main reasons why we chose RF are 1) their ability to handle very large number of input variables even for very small datasets and 2) the ensemble technique has shown to outperform the base classifier, which in this case would be a decision tree. The strength of a RF classifier depends on the accuracy of individual trees and the level of independence (or correlation) between the trees. As we increase the number of trees in a RF, the likelihood of dependence between the individual trees increases making the forest weaker. Hence it is important to determine the proper balance between the number of trees and classification error. To achieve this goal, we performed classification on the dataset using RF with 5, 10, 50, 100, 150, 200 and 250 trees. We performed a Wilcoxon signed rank test to determine at what point adding more trees to a forest did not yield any statistically significant improvement in classification accuracy. RF performs feature selection during training. This provides useful information about the importance of each feature for the classification accuracy. We report the top 3 features selected for each observation. We used the implementation of RF from the Weka Machine Learning toolbox [7].

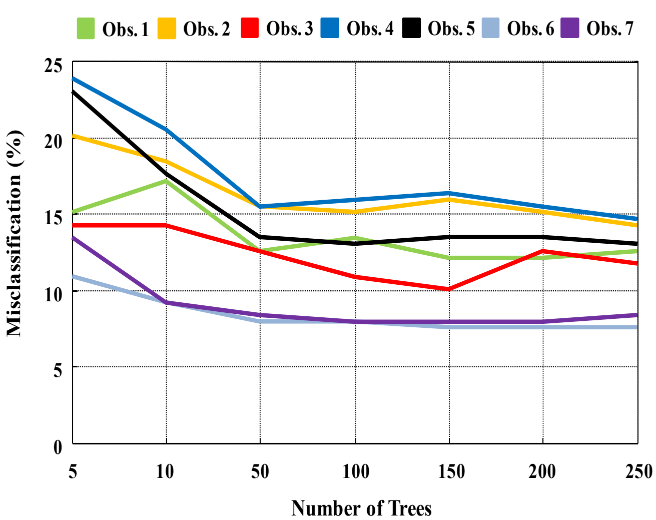

Fig 2. Misclassification changes depending on the number of trees in the Random Forest classifier. Results are shown for observations 1-7 of the Edinburgh Visual Scale.

III. Results

Our first step was to find a number for trees in the RF that provided good classification accuracy. Figure 2 shows the classification error with respect to the number of trees in the RF. We found that at 5% significance level there is no improvement in classification accuracy when the number of trees is increased from 50 to 100 and beyond.

Table 3 shows the classification results obtained with a RF with 50 trees. We see that observation 1, has a low classification error. We can also see that the classifier performs best for observations 3, 6 and 7, which are related to the amount of ankle dorsiflexion in different phases of the gait cycle. In contrast, higher classification errors are found for observations (4 and 5) that are meant to capture rotations of the foot in the frontal and transverse planes. For all the observations, the classification error is smaller than 20%. RF provides internal estimates of generalization error [6]. The maximum generalization error of 18% was seen for observations 2 and 4. The generalization error for observation 1 was about 4% higher than the classification error in Table 3.

TABLE 3
RANDOM FOREST CLASSIFICATION WITH 50 TREES

Observation	Classification Outcome (%)
1	87.45 %
2	84.52 %
3	87.44 %
4	84.52 %
5	86.61 %
6	92.05 %
7	91.63 %

TABLE 4
RANDOM FOREST VARIABLE IMPORTANCE

Observation	Feature I	Feature II	Feature III
1	1	16	4
2	4	16	14
3	15	17	16
4	20	16	14
5	20	21	14
6	20	21	14
7	16	15	17

Table 4 shows the top three ranked features for each observation. We can see that throughout all seven observations the top features picked by the classifier reflect aspects that correlate well with the clinical observations. For example, we can see that the three most important features for observation 3 and 7 are derived from the ankle kinematics during stance and swing. Also, feature 16 (Max Ankle Dorsiflexion in Swing) is important for observation 1 and 2, along with feature 4 (Path Length/AP displacement), which represents a measure of linearity in the CoP trajectory.

TABLE 5
AVERAGE CONFUSION MATRIX

%		Classified as		
		0	1	2
Actual Score	0	83.8 +/- 11.1	14.4 +/- 9.6	1.8 +/- 4.4
	1	14 +/- 18.2	80 +/- 16.2	6 +/- 6.7
	2	0	15.3 +/- 9.4	84.7 +/- 9.4

Table 5 shows an average confusion matrix (mean and standard deviation) for the first 7 observations of the Edinburgh Visual Scale. The misclassified instances are mostly concentrated at boundaries between adjacent classes. To put it simply, the likelihood of a 0 being classified as a 1 is higher than it being classified as a 2. This is important because the progression of the gait abnormality is gradual, so the actual distribution of the features across subjects is a continuum whereas the clinical scale is discrete.

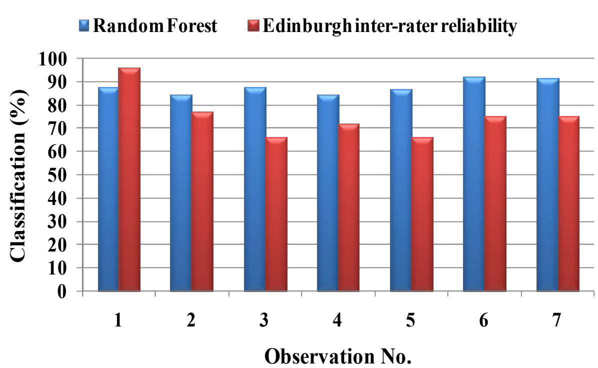

Fig 3. Comparison between the Inter-rater reliability of the Edinburgh Visual Scale and the classification outcome of the Random Forest for observation 1-7.

In Figure 3, we can see the results of the classification performed with a RF with 50 trees compared to the inter-rater reliability reported by Read et al. [5] for the Edinburgh Visual Scale. The accuracy of the RF classifier is comparable to the percentage agreement among raters using the observational scale.

IV. Discussion

In this paper, we showed that using features extracted from CoP trajectories and ankle kinematics, we can build a classifier that can predict the severity of toe-walking in children with CP with accuracy comparable to the inter-rater reliability of the Edinburgh Visual Scale.

We found that there was no significant increase in classification accuracy when using a Random Forest classifier with more than 50 trees. The results obtained with a Random Forest with 50 trees revealed that across all observations the classification error was always smaller than 20%. Increasing the number of trees beyond 50 would only lead to an increase in correlation or dependence between individual trees which can lead to increased generalization error.

Our classification accuracy decreased on the observations related to the rotation of the foot in the frontal and transverse planes. This is not surprising as it is difficult to capture such information using features extracted from the CoP.

We anticipate that the approach we have developed can be successfully implemented with existing sensorized shoe devices [8]. The output of a sensorized shoe incorporating instrumented insoles and bending sensors, combined with classifiers of the type we have developed, would allow accurate field monitoring of children with CP leading to better overall management of their gait impairments. In the future, we hope to expand our analysis on a broader range of gait deviations exhibited by children with CP (e.g. crouch gait).

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