Markerless Motion Analysis for Early Detection of Infantile Movement Disorders

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Abstract— **The analysis of spontaneous movements provides valuable information for diagnosing infantile movement disorders. However, analysis is time-consuming and interpretation requires well-trained experts. We present an automated system that captures 3D joint positions and head rotation of infants without attached markers or sensors. We introduce motion parameters of head, trunk, upper and lower limbs of both body sides that are related to range, variability, and symmetry of motions and offer objective diagnostic information for assessment of motor behavior. We analyze 6 recordings of 5 infants who are at high-risk of impaired motor development, and show how the system highlights movement characteristics that hint at disorders.**

Keywords— **Motion analysis, infants, diagnostics**

I. Introduction

Recent studies show that delays and perturbations of motor development affect up to 12% of infants, depending on the time of examination [1]. While a multitude of causes and symptoms exists, early intervention can dampen the effect of impairments [2]. Clearly, the step preceding intervention has to be detection. However, detailed neurological examination requires time and expertise, and is therefore only performed if justified reasons for its necessity have been found. An automated system can help to discover infants who would benefit from early diagnostic and therapeutic action. For wide-spread use, it is required to be cheap, easy to use, unintrusive to the infants and it has to provide objective measures.

We propose a system that only depends on a commodity depth sensor (e.g. Microsoft Kinect) and a connected laptop (see Fig. 1). It requires no calibration or attachment of markers or sensors to the children. We build upon a recently introduced system for body pose estimation in depth images using random ferns [3]. We capture 3D body joint positions and head rotation over time, to calculate a variety of motion parameters related to range, variability and symmetry of movements.

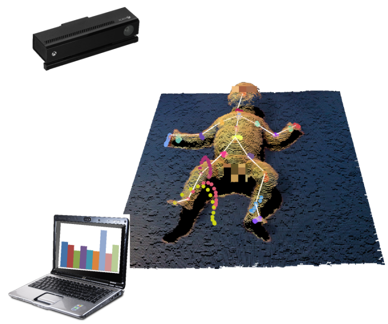


Fig. 1: System setup. A depth camera captures an infant lying on an examination table. The system running on a connected laptop estimates 3D joint positions and head rotation and provides diagnostic information for the assessment of motor development.

II. Related work

Several systems have been proposed for the task of detecting infantile movement disorders, especially cerebral palsy, based on motion analysis. Some rely on sensors or markers that are attached to the infant, which often requires calibration, is intrusive to the infant, and can involve cost-extensive hardware [4, 5], while others use optical flow-based methods relying on 2D video data [6]. The introduction of the Microsoft Kinect sensor has triggered a lot of research on human motion analysis using depth sensors [7]. The minimum size of 1 m for the integrated body tracking prevents it from applications to infants. However, the provided depth data can be utilized to capture an infants' pose in 3D, e.g. by fitting a simplified body model [8] or a model of the lower limbs [9] to depth images. Extracted features used for the assessment of movements include parameters based on trajectories, angles and velocities, stereotypy score, or frequency analysis. A detailed survey of existing systems can be found in [10].

III. Methods

Our system is based on an approach that estimates 3D positions of 21 body joints in depth images using a variant of random decision trees [3]. We give a brief overview of the system and refer the reader to [3] for more detailed information about methods and accuracy of the approach.

A 3D body model is textured with colors corresponding to 21 different body parts (Fig. 2, right), and animated in a wide variety of poses. Labeled depth images generated from this model serve as training data to create an ensemble of random ferns [11] for pixel-wise body part classification. We capture data of infants lying on an examination table, consisting of depth images and registered RGB information. We segment the background of the scene by fitting a plane to the table in the depth image, and only keep pixels that are part of the infant. The ensemble of ferns assigns a body part label to each of the remaining pixels, and, after a filtering step, 3D joint positions are calculated from body part regions.

We use a convolutional neural network from C++ library dlib [12], that is trained using the max-margin object-detection loss function [13] to detect the infants' face in each 2D RGB image. We use a shape predictor [14] from the same library to find 68 facial landmarks in the detected face region, from which we extract the centers of the eyes. We project the 2D eye coordinates from the registered RGB images to the 3D point cloud constructed from the depth image. We calculate the head rotation as the angle between the line through the center between the eyes and the detected head joint position, and the plane that is defined by the head joint and the main body axis, and is perpendicular to the table plane. An example of estimation of pixel-wise body part labels and head rotation is given in Fig. 2, left.

Fig. 2: Left: Estimated head rotation and pixel-wise body part labels. Pink dots depict eye positions, white line the viewing direction. Right: Ground truth labels. 21 different body parts are encoded by colors.

IV. Motion parameters

The benefit of motion parameters introduced in this section is two-fold. First, the parameters provide objective diagnostic information and can serve as an assistive tool for neurological examination. Second, they describe movement characteristics with the capacity of highlighting possible impairments and can therefore automatically detect infants in need of further examination. The parameters are chosen to describe range, variability and symmetry of motion of arbitrary body parts. We measure values that depend on single body joints:

- velocity
- acceleration
- distance traveled
- distance to the table
- volume covered: volume of convex hull of joint positions of all frames
- percentage of frames in which motion is present ($velocity > threshold$)

Parameters related to head rotation are:

- number of head rotations
- percentage of frames in which the head is rotated towards the left / right side
- mean and standard deviation of head rotation angles

Measurements depending on multiple joints are:

- angles
- ratio between parameter values for left / right body side
- percentage of frames in which hands / feet / left side / right side / all extremities move together

We calculate motion parameters based on the above measurements. The parameter for traveled distance of an extremity d_tr_{extr} is the sum of euclidean distances between joint positions in consecutive frames per minute:

$$d\_tr_{extr} = \frac{1}{t} * \sum_{i=2}^{n} ||x_i - x_{i-1}||, \tag{1}$$

where $extr$ denotes the extremity, t is the duration of the recording, x_i the 3D joint position in frame i, and n the number of frames in the recording. $||\cdot||$ denotes the euclidean distance. The parameter describing the change in distance to the table of an extremity d_table_{extr} is defined by

$$d\_table_{extr} = \frac{1}{t} * \sum_{i=2}^{n} ||dist(x_i, tp) - dist(x_{i-1}, tp)||, \tag{2}$$

with $dist(x_i, tp)$ specifying the distance of the joint position of the extremity to the table plane in frame i. The left-right ratio of a parameter $ratio\_lr(par)$ describes the factor by which the parameter value for one body side is larger than the value for the other side:

$$ratio\_lr(par) = \frac{max(par(l), par(r))}{min(par(l), par(r))}, \quad (3)$$

where $par(s)$ specifies the summed values of parameter par for body side s.

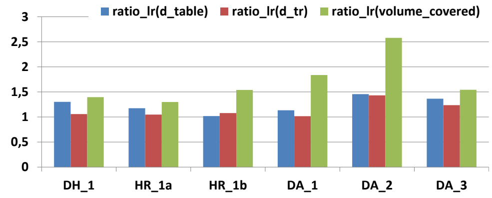
V. Evaluation

We present 6 sequences of 5 infants, lying in supine position without external stimulation. All of them were awake and in a cooperative mood at the time of recording. Ethical approvement (Ludwig-Maximilians-Universität Munich) and parents' written consent was obtained prior to recording. A subset of 9 parameters is selected from the full parameter set (Sec. IV.), and evaluated on the recorded sequences (Fig. 3).

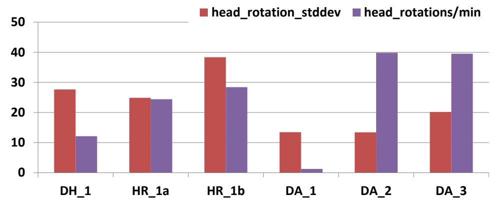
Definitely healthy patient (DH_1) is a former preterm infant, born at 35+4 weeks of gestational age (WGA). At the time of recording, the patient is 14 weeks of corrected age. The patient shows head and trunk position close to midline, visually exploring the environment with normal head movements to both sides. All limbs move independently from each other and there are no stereotypical movement patterns. Fidgety movements are observed, representing age-corrected adequate gross motor development (RGB video - data not presented). Fig. 3a (DH_1) shows comparable spontaneous activity of left and right upper and lower extremities with ratios close to 1. Head rotation intensity and frequency is unremarkable (Fig. 3b). The amount of movement is higher in lower than in upper limb (Fig. 3c).

High Risk patient 1a (HR_1a) is a former preterm infant, born at 25+2 WGA. At the time of recording the patient is 12 weeks of corrected age. Head and trunk are in midline position with a slight rotational predominance to the right. No significant symptoms of abnormal gross motor development besides a mild positional asymmetry of head rotation towards the right side are observed in RGB video (not presented). Fig. 3a (HR_1a) displays no significant lateralisation of spontaneous arm or leg movements. Head rotational parameters are without remarkable differences (Fig. 3b), and a high amount of motion in all limbs represents a very active baby (Fig. 3c).

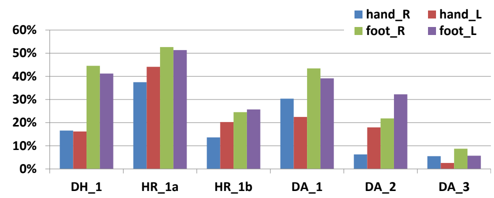
High Risk patient 1b (HR_1b) is the same patient as HR_1a, but at follow-up 4 weeks later. The previous preference of head rotation to the right has decreased to almost midline (RGB video - not presented). Fig. 3a (HR_1b) displays a mild lateralisation of volume covered by spontaneous movements comparing left and right sides. Head movements have increased (Fig. 3b), while limb movements have decreased compared to the prior analysis, with again predominance of the lower limbs, representing a less active infant (Fig. 3c).



(a) Ratio left-right (distance to table), ratio left-right (distance traveled), ratio left-right (volume covered).



(b) Head rotation parameters per recording. Standard deviation of angles in degrees, number of head rotations per minute.



(c) Percentage of frames in which motion is present, indicated for each of the extremities.

Fig. 3: Evaluation of 9 parameters within 6 recordings of 5 infants showing different movement patterns. Details in Section V. Best viewed in color.

Definitely abnormal patient 1 (DA_1) is a term-born infant, who is 14 weeks of age at the time of recording and has an obvious cognitive impairment. A neurological examination resulted in diagnosis of a genetic syndrome including muscle weakness and muscular hypotonia. The infant shows an apparent lack of head rotation which is caused by the weakness of neck muscles and lack of interest in the environment (Fig. 3b, DA_1). The head cannot be held in the truncal plane, leading to spontaneous positioning to the left (RGB video - not presented). The asymmetrical tonic neck reflex limits the mobility, especially of the right arm, and causes a large difference in volume covered by left and right body side (Fig. 3a). Weakness is predominantly present in the head, neck, and arms, while the legs are able to lift off the ground much easier, with again asymmetric distribution (Fig. 3c).

Definitely abnormal patient 2 (DA_2) is a term born infant with generalized hypotonia due to a genetic syndrome, who is 34 weeks of age at the time of recording. The most obvious impairment is muscle hypotonia, but the infant has a good (age-adequate) mental state. Similar to DA_1, there is a significant lateralisation in spontaneous movements of the upper limbs (Fig. 3a). In contrast to DA_1, head movement is much better, as neck strength is sufficient to rotate the head, and the patient is interested in visually exploring the environment (Fig. 3b). A predominance of motions of the lower limbs and the left body side is indicated in Fig. 3c, but with a remarkably reduced amount of motion compared to DA_1.

Definitely abnormal patient 3 (DA_3) is a former preterm infant, born at 23+4 WGA. At the time of recording, the patient is 13 weeks of corrected age. Cranial MRI demonstrated intracranial hemorrhage III$^\circ$ on both ventricles, as well as signs of bilateral periventricular white matter lesions, leading to the diagnosis of bilateral spastic cerebral palsy. The muscle tone is generally increased on both upper and lower limbs. Head control is reduced, but possible, while the trunk is hypotonic. The patient is not able to open his hands actively and shows significantly reduced spontaneous, and stereotypical, generalized movement patterns of the upper and lower limbs (RGB video - not presented). Although there is hardly any spontaneous activity of the patient (Fig. 3c), there are no significant differences in movement distance and volume covered when comparing left and right upper limb (Fig. 3a). Head rotations are within normal ranges (Fig. 3b).

VI. Conclusion

We presented a system for markerless 3D motion analysis that is unintrusive, cheap, and easy to use. It provides automatically detected, objective measures during spontaneous activity of infants. It can be used to support the diagnosis of abnormal motor behavior due to a variety of different pathologies. We demonstrate how 9 representative qualitative and quantitative movement parameters allow to detect clinically meaningful differences between healthy and impaired infants between 12 and 39 weeks of age. The infants in this pilot study are selected from a tertiary care high risk infants outpatient clinic. In the next phase, we will expand our analysis to healthy infants across different age groups in order to objectify the age-adequate healthy range of the selected movement parameters.

Conflict of Interest

The authors declare that they have no conflict of interest.

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