Quantitative Approaches for Detecting Early Childhood Developmental Disorders using Wireless Sensors and Mobility Data

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***Abstract*— As estimated by the World Health Organization (WHO), 5% of the world's children population are diagnosed with an early developmental disability such as autism and cerebral palsy. State-of-the-art clinical diagnostic procedures are predominantly dependent on observational assessment by a trained physician. Physicians assess the severity of the disability by observing the child as well as by considering the feedback from the parents. However, as the final decision is completely dependent on the observer the procedure becomes subjective and does not provide an accurate decision. Moreover, such approaches are time-intensive and require enormous human effort. Hence, it is essential to explore the alternative opportunities that provide an accurate assessment. Recent studies show that abnormal motor skills are often the initial signs of later developmental disorders. This paves the way for exploring alternative opportunities to identify the disease in the early stages of childhood. Although different methods for collecting neonate motor data have been explored in the past, improvements in sensing technologies facilitate convenient as well as unobtrusive methods to collect the mobility data even from the infants and be able to detect the abnormality in the motor movements. Since wearable devices are tiny and easy to use in collecting motor data from neonates, it is feasible to distinguish abnormal motor development from normal motor development. Thus, mobility data collection from an infant using a wearable sensor is beneficial in the early diagnosis of developmental disabilities like cerebral palsy. Our main contribution to this study is to present the analysis of various wearable sensor-based motor assessment methods in predicting childhood disorders. This article first presents some of the existing clinical diagnostic procedures and then elaborates on mobility-based quantitative assessment methods. Furthermore, this document presents various crucial mobility parameters associated with identifying childhood disorders.**

Keywords- mobility; childhood developmental disorder; wearable sensor.

I. Introduction

In recent years, the prevalence of developmental disorders among children is rising at an alarming rate. Autism Spectrum Disorder (ASD), Cerebral Palsy (CP), and Attention Deficit Hyperactivity Disorder (ADHD) are the most common disorders that infants are affected in the USA [1]. According to the World Health Organization (WHO), around 5% of the world's children population aged under 14 years are afflicted with a moderate to severe disability [2]. Early childhood developmental disorder is one of the primary causes of children being referred to primary healthcare clinics [3]. Chronic or perpetual delays in one or more motor functions of the child can be treated as a development disorder [4]. The onset of the disability may occur regardless of racial, ethnic, and socioeconomic groups. The manifestation of motor disability is caused by atypical brain development. Yet, specific reasons for atypical brain development are not known [5]. Research shows that preterm birth and pregnancy complications that occur in the perinatal period may affect the brain. Consequently, babies born in this category are at risk for neurodevelopmental impairments [6]. Additionally, low birth weight and infections during pregnancy are a high risk for several developmental disabilities. According to the study conducted by National Health Interview Survey (NHIS) in the United States, the growth of childhood disorders has increased to 17% between the years 2009 and 2017. Also, one out of six children between the age groups 3 and 17 years have one or more disabilities [7]. Furthermore, ADHD, ASD, and CP are the common disorders found among children and boys were more likely to be in the vulnerable group than girls [4].

Although there is no standard laboratory test for identifying developmental disability in high-risk neonates, several researchers have proposed diagnostic guidelines for each disorder individually. For instance, Case-Smith introduced Posture and Fine Motor Assessment of Infants (PFMAI) for identifying developmental delays by observing neonate's motor movements [8]. Similarly, Prechtl's assessment for detecting CP and The Alberta Infant Motor Scale (AIMS) for assessing gross motor development are some of the observation-based diagnostic methods [9][10]. Nevertheless, most of these procedures offer subjective evaluation and are solely judged by a trained practitioner. Furthermore, children need to be taken to specially designed laboratories multiple times. Therefore, it is crucial to implement an objective technique that can accurately identify the developmental disability.

The evolution of fine and gross motor skills in children with atypical neurodevelopment is more cramped than in children with typical neurodevelopment. As a result, affected children do not acquire smooth limb movements but rather rigid and nonsynchronous [11]. Often, delays in acquiring sufficient motor movements are the early signs of later developmental impairment. Hence, an infant's motor assessment can be a potential parameter for the early diagnosis of the disability. Moreover, significant research is going on towards the assessment of an infant's motor function as a method to detect developmental disorders, such as CP, and ASD [4][7][11]. The sooner the disorder is diagnosed the better the possibility for effective intervention therapy.

The main motivation of this study is to describe some of the existing clinical procedures to determine the onset of the disability. Then elaborate on wearable sensor-based diagnostic methods in identifying the various developmental disorders by utilizing the motor movements of infants. In this document mobility and motor, movements are used interchangeably. The remaining sections of the document are structured as follows. In Section II, the study methodology is discussed. Section III explains various qualitative assessment methods. different types of wearable devices used for mobility data collection are elaborated in section IV. In section V, the mobility-based quantitative diagnostic approaches are presented. Important mobility parameters that have been explored by the scientific community are highlighted in section VI. Under Section VII, various aspects of mobility-based assessment methods are elaborated. Finally, Section VIII concludes with a summary of this work.

II. METHOD

In the past decade, there has been a substantial rise in the quantitative assessment of motor dysfunction by attaching tiny sensors to neonates' upper and lower limbs. Abnormal movements are characterized by repetitive, stereotyped movements, rigid movements due to lack of smoothness, and unusual gait patterns [6]. These atypical patterns are distinguishable by processing the mobility data collected from the sensors attached to a child's limb. Researchers have also concluded that abnormal movements are strongly correlated to their abnormal brain development [12]. The goal of motor assessment is to quantify the degree and range of motor disability and predict whether the child falls under the stage of Typical Development (TD) or At Risk (AR).

The primary purpose of this document is to review the various mobility assessment methods that were employed for diagnosing early childhood developmental disorders. At first subjective methods are discussed then wearable sensor-based assessment methods are elaborated. For this study, literature has been chosen, which includes different aspects of early childhood disorders. The literature study criteria are explained in detail in Fig. 1.

III. BACKGROUND

This section illustrates various subjective methods that detect developmental disability in early childhood. These methods can be broadly categorized into two types: milestone-based assessment methods and observer-dependent methods. To discuss further three generalized developmental stages are defined.

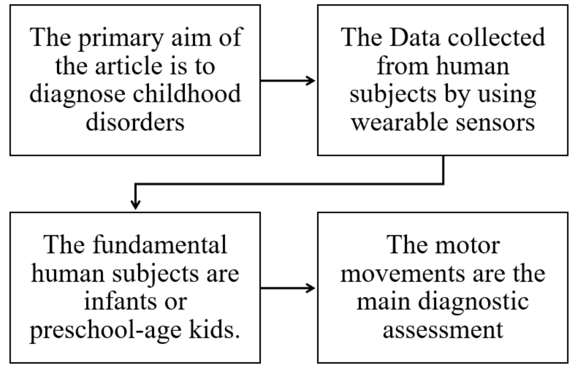

Figure 1: Study procedure

At-Risk (AR): Neonates born preterm and with pregnancy complications are considered At Risk (AR) of developing aberrant motor function and eventually likely to be diagnosed with developmental disorders including CP [4].

Typically developing (TD): Infants with normal limb movements are classified as Typical Developing (TD) [4].

Neurodevelopmental disorder (NDD): Children who are already diagnosed with any developmental disorders like CP, ASD, and ADHD are categorized as infants with NDD [13].

A. Milestone-based assessment Methods

Milestone for a child is considered as what most babies do by that age. Milestone-based assessment is the simplest method that facilitates in early detection of the disability. The development in the early infantile years is crucial for the lifelong growth of every child. Therefore, the first 36 months are very important to check and recognize if there is any lag in acquiring any development [14]. Typical growing children develop in five major categories: (1) cognitive, (2) social and emotional, (3) speech and language, (4) fine motor skills, and (5) gross motor skills. Delay in acquiring one or more of such skills can be considered a developmental disorder.

According to the CDC [4], TD child reaches certain developmental milestones as they grow. For instance, in most, the 6 months old babies begin to roll over and recognize their parent's faces. Likewise, a 12-month-old toddler should be able to sit without any help and exhibit variable limb movements. However, AR infants lag in acquiring one or more such skills. Trained physicians and practitioners recommend using developmental surveillance and screening process as an early intervention to identify the disabilities [14]. It is a longitudinal and continuous process where infants' growth is carefully observed. Often, clinicians assess the type and severity of the disability by integrating the feedback questionnaire from parents as well as the child. Though it is the initial diagnostic method used by the practitioners, it is time-intensive and requires continuous monitoring of the child for several days.

Moreover, the probability of missing certain guidelines is very high. Hence, clinicians are interested in developing standardized clinical guidelines that can identify the disorder as well as quantify the severity of the disorder.

B. Observation-dependent Methods

Traditional assessment is heavily dependent on visual observation by a trained physician. Sometimes physicians prepare a questionnaire and assess the level of abnormality by integrating the feedback from the parents and/or the child. In such a scenario, parents might be unaware of specific symptoms that the child is suffering, and the child may not be able to give precise feedback as adults. Hence, the decision-making becomes more complex. Additionally, existing clinical methods, such as analysis of neuroimaging require a trained consultant physician. But reliability and accuracy are largely depending on the expertise of the consultant. Besides the inherent complexity in judging the presence of the disorder, estimating the severity of the illness is far more challenging. The inception of qualitative assessment of the infant's nervous system is indeed a breakthrough in the diagnosis of developmental disorders.

The Alberta Infant Motor Scale (AIMS) [9] is one of the early observational scales to assess the neonate's gross motor function. In this method, a rating will be calculated based on the infant's performance in weight-bearing, posture, and antigravity movements. This method can be used only for babies under 18 months of age and the observer needs extensive training in the respective assessment. Prechtl et al. [10] proposed another observation-based systematic methodology termed General Movement Assessment (GMA) for diagnosing CP. They have postulated that the quality of General Movements (GMs) is cramped and lacks smoothness over time due to impaired brain development. The absence of GMs may be observed in the video recording of an infant. This approach also does necessitate training by experts. In another experiment [15], Heineman et al. developed a video-based mobility evaluation technique, the Infant Motor Profile (IMP), that can differentiate between kids between TD and AR neurodevelopment. The downside of all these methods is that it involves an enormous human effort to examine the video recording for accurate prediction. Melbourne Assessment of Unilateral Upper Limb Function-2 (MA-2) is a standard reference tool to measure the quality of upper limb movements in kids with atypical brain growth aged between 2 to 15 years [16]. Moreover, scoring is estimated based on how a child performs 14 test activities including pickup and release of some objects. Likewise, there are numerous subjective motor assessment methods including the Bayley Scale of Infant and Toddler Development [17], Neuro Sensory Motor Development Assessment (NSMDA) [18], and Test of Infant Motor Performance (TIMP) [19].

However, rating-dependent approaches have various shortcomings. (1) Assessment is entirely observer-dependent. Consequently, there is a high probability that the observer is wrong in his estimation. (2) Evaluation is time-intensive and consumes immense human effort. (3) The observer is required to be trained in advance with the necessary skills to make an optimal conclusion. After the training, it takes substantial time to acquire proficiency in the diagnosis. (4) Patients must visit the physicians and laboratories frequently. (5) Often, laboratories must have a specialized environment and equip with expensive tools. (6) Monitoring the rehabilitation of the affected infants is challenging because of the dependency on the observer. (7) Children's attention span is very limited, and so they can easily get annoyed with cumbersome instructions. Hence, to overcome these limitations, it is essential to have an observer-independent approach.

IV. MOBILITY AND DEVICES

Characterizing the atypical motor movements including repetitive and stereotypical patterns is crucial in the early diagnosis of neurodevelopmental disease. A qualitative examination of neonate movements necessitates a special skill set and the outcome varies from observer to observer [20]. To fill the gap, sophisticated systems, such as stereo photogrammetric movement analysis, gaze-tracking devices, and 3D motion tracking with passive markers [21] were introduced. Yet, these methods require an expensive structured setup with many wires and sensors to monitor the baby's physical movements. Wearable technology made it possible to collect the movement data by attaching tiny sensors to the body parts of the infants without major disturbance.

In recent times, Inertial Measurement Units (IMUs), also known as inertial sensors have been increasingly explored by numerous researchers. Typical IMUs comprise of accelerometer and gyroscope and occasionally include a magnetometer. Nevertheless, many scholars have employed an accelerometer-based sensor to acquire infants' arm and leg movements [6][22][23]. Wearable instruments are suitable for monitoring the limb movements of infants because of their flexibility in sensor placement, adaptability, and power efficiency. Since the human subject is an infant, sensors are usually embedded in an appropriate peripheral, such as leg warmers [12], and wristwatches [24]. In some studies, skin-adhesive sensors have also been used [25]. Although the device has a variety of sensing technology, the aim is to collect the movement data unobtrusively without creating considerable discomfort for the babies. Therefore, wearable sensors are efficient for the objective assessment of children's movements. Table 1 shows various wearable sensor devices employed in collecting mobility data from children.

Nowadays, wearable devices are compact and come with internal storage as well as a provision to connect and upload the data to cloud storage on the go. Most of the devices are battery-operated, eliminating cumbersome wires and cables. When multiple sensors are included in the data collection process, then all the sensors must be actively synchronized

TABLE 1: Various wearable sensors employed in collecting the mobility data

Reference	Sensor name	Components	Make	Sensor placement	Type of data	Type of movement
[6]	Cloth band sensors	Accelerometer	Custom designed	Wrist, ankles, and forehead	Raw sensor data	Limb and head movements
[12,26,28, 27, 31]	APDM Opal sensor	3D-accelerometer, 3D-gyroscope, and 3D-magnetometer	APDM	Left and right ankle	Raw sensor data from all directions	Leg movements
[21]	WAMS	Inertial-magnetic MAG3 sensor, Analog-to-Digital Converter	Custom designed	Wrist and ankle	Raw channels converted by ADC	Wrist and ankle movements
[23]	ETH orientation sensor	Accelerometer and Gyroscope	Custom designed	Predefined body movements	Raw sensor data	Limb and head movements
[24]	Bracelet sensors	Accelerometer	Custom designed	Both wrists	Raw sensor data	Right and left wrist movements
[25]	MetamotionC sensing board	Accelerometer, Gyroscope, and Magnetometer.	Mbientlab	Wrist, ankles, and forehead	Raw sensor data	Limb and head movements
[29]	Actiwatch	Modified Accelerometer	Mini Mitter	Right ankle	Activity count	Right leg movements
[30]	Axes of the accelerometer	Accelerometer	Freescale semiconductor	Hands and ankles	Raw sensor data	Both hands and leg movements

throughout the duration. It then allows data to be collected continuously from all sensors, even outside the laboratory environment, such as at home. Primarily, these devices are used to record upper and lower limbs that will help characterize the disorder. Although numerous instruments, such as gaze tracking devices, are available to collect mobility data, not all may be suitable for infants. Furthermore, setting up such a piece of equipment requires a well-structured and perfectly controlled laboratory environment. The wearable devices are an ideal replacement for infants that can facilitate accurate measurement of motor movements [21]. In addition to this, wearable devices are wireless and create a friendly ecosystem for little kids. Wearable devices come at affordable prices that make it easy to attach multiple sensors simultaneously to record all the baby's movements. Fig. 2 presents the convenient body locations where sensors can attach. And different impaired movements are shown that are characterized as aberrant motor movements exhibited by the disordered children.

V. MOBILITY-BASED ASSESSMENT METHODS

Measuring abnormality from the child’s movements is an important clinical task as it reduces the significant human effort in identifying the impaired motor skills. Further, it helps physicians to come to an objective conclusion. With the latest advancements in wearable devices, it has become easy to attach them to infants and collect the data continuously. Various quantitative motor assessment studies are summarized in Table 2. This study includes the research that has employed wearable sensors and finds the quantitative measurement of the children's motor movements.

A few scholars had endeavored and developed unobtrusive and non-invasive wearable instruments suitable for infants and toddlers. As early as 2008, Campolo et al. [21] prototyped a wearable sensing system for monitoring the upper and lower limb spontaneous movements of premature babies. Their sensing instrument can be used in infants as young as 2 weeks. They have hypothesized that abnormal movements are the early signs of later developmental disorders, such as ASD. Redd et al. [25] carried a pilot project on a single healthy born infant to assess the General Movements (GMs) and Fidgety Movements (FMs) [10]. They have built a wearable monitoring system with an array of sensors to acquire the infant movements for both the short and long-term. Their results show that the absence of variability in GMs and FMs might be the early sign for the manifestation of neurodevelopmental disorders, such as CP. Nonetheless, they have experimented with only one healthy infant.

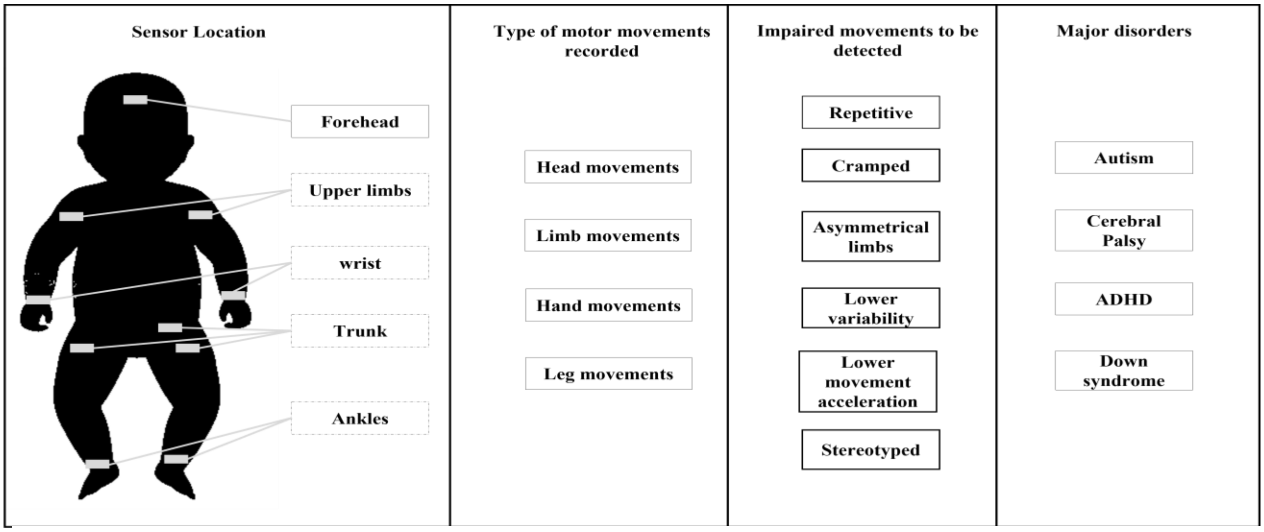

Figure 2: Wearable sensors based quantitative diagnosis

TABLE 2: SUMMARY OF MOBILITY-BASED ASSESSMENT METHODS

Reference	Purpose	Sensor	Sensor placement	Wear time (in hours)	Setting	Disorder	Movement type	Subjects	Age (in months)
[6]	Predict impaired motor activity	Accelerometer	Head, ankles, and wrist	1	Clinical	CP	Spontaneous head, leg and arm movements	10 AR	<3
[12]	Classify TD and AR	IMU	Ankles	8-13	Natural	NA	Spontaneous leg movements	12 TD 19 AR	1-15
[21]	Early diagnosis	IMU	Wrist and ankles	NA	Clinical	ASD	Spontaneous leg and arm movements	NA	NA
[22]	Measure variability of movements	IMU	Ankles	8-13	Natural	NA	Spontaneous leg movements	11 TD 20 AR	6-9
[23]	Predict motor disorder	Accelerometer and gyroscope	Trunk, upper and lower limbs	4	clinical	CP, stroke	Predefined body movements	4 AR	9-12 years
[24]	Clinical vs motor assessment	Accelerometer	wrist	75	Natural	CP	Spontaneous upper arm movements	26 TD 26 AR	1-17 years
[25]	Diagnosis CP	IMU	Forehead, ankles, and wrist	1 min	Clinical	CP	Spontaneous head, leg, and arm movements	1 TD	3-5
[26]	Classify TD and AR	IMU	Ankles	8-13	Natural	NA	Spontaneous leg movements	12 TD 19 AR	1-16
[27]	Quantify leg movements	Inertial sensor	Ankles	8-13	Natural	NA	Spontaneous leg movements	12 TD	1-12
[28]	Diagnose ASD	IMU	Ankles	8-12	Natural	ASD	Spontaneous leg movements	5	3-12
[29]	Assess leg movements	accelerometer	Right ankle	48 hrs. x 4 times	Natural	DS	Spontaneous right leg movements	8 TD 8 AR	3-6
[30]	Diagnose CP	Accelerometer	Ankles and wrist	20 min	Clinical	CP	Spontaneous leg and arm movements	19 TD 4 AR	<10
[31]	Number of days required for assessment	IMU	Ankles	5 days	Natural	NA	Spontaneous leg movements	16 AR	2-14

Typically developing (TD) neonates demonstrate rich leg movements by embedding tiny sensors inside custom-designed leg warmers. Moreover, the researchers aimed to classify the group of infants into TD or AR from the day-long (8-13 hours) leg movements data. They also analyzed sensor data recorded from AR infants and were able to distinguish between AR babies with poor and good development. In [26], Goodfellow et al. developed binary classification algorithms to predict whether the child is TD or AR. In this approach, a group of 22 infants aged between 0 to 12 months was divided into two groups 0-6 months and 6-12 months. Then, the researchers extracted two sets of features for each group and found a significant difference between TD and AR mobility data of 0-6 months than from 6-12 months. Their findings prove the importance of early childhood diagnosis. Often, it is critical to categorize between TD and AR during early infancy. Abrishami et al. [26] quantified infants' spontaneous groups as 0-6 months and 6-12 months. Then, extracted two sets of features for each group and found a significant difference between TD and AR mobility data of 0-6 months than from 6-12 months. Their findings prove the prominence of early childhood diagnosis.

Similarly, numerical estimation of abnormal mobility has also been studied in the past as it helps in distinguishing both healthy and impaired infants. One of the early experiments [6], utilized a simple accelerometer sensor and was able to collect the data from the premature neonates recruited from the NICU, who are potentially at risk of CP. Then, by extracting features and applying the machine learning technique including Decision Trees. The researchers were able to recognize the abnormal movements namely Cramped-Synchronized General Movements (CSGMs) [10]. According to Prechtl's assessment for CP [27], the presence of CSGM is an early marker for lateral developmental disorders. Wilson et al. [28], formulated Motion Complexity (MC) by measuring the variability from the infant's leg movement data. They conjectured that infant with lower MC is at risk (AR) of disabilities, such as ASD. Moreover, AR subjects compose lower motion complexity compared to TD subjects because their actions are repetitive and stereotyped. Smith et al. [22] proposed Sample Entropy (SampEn) as a function to measure the variation and repetition in kids' leg movements. Additionally, SampEn is lower for infants with developmental delays than normal infants. A different experiment carried out by Hoyt et al. [24], assessed only upper limb movements and recommended two metrics: The Use Ratio (UR) to measure the quality of using both arms and the Mono Arm Use Index (MAUI) for quantifying intensity and frequency of each arm. Their results signify that UR and MAUI are lower for typically developing children and higher for children with developmental delays.

Furthermore, many scientists are interested in studies specific to a particular disorder like CP and Down Syndrome (DS). McKay et al. [29] conducted a mobility assessment of a group of infants with DS and without DS. Using an activity monitor attached to the baby's right ankle measured leg activity and sleep patterns at 3,4,5, and 6 months. Their statistical analysis observed a significant group difference between the infants with DS and without DS with respect to their motor components. Strohrmann et al. [23] acquired mobility data from four children (2 diagnosed with CP and 2 with stroke) undergoing rehabilitation. In this work, they were invited to perform a set of predefined motor tasks and the progress in rehabilitation therapy was measured using extracted features including smoothness in the upper and lower limb movements, and coordination between both arms. Another study [30], proposed an objective assessment methodology to diagnose CP from the spontaneous leg and arm movements of newborn babies. Their method is built on a decision tree classifier algorithm and achieved ~90% accuracy. Further, they have posited that their methodology can be easily adapted by the clinical practitioners and helps to monitor the progress of rehabilitation.

A different experiment performed by Deng et al. [31] assessed the motor behavior of neonates to determine the minimum number of days required to characterize the ideal daily leg movement patterns of children who are at risk of developmental disorders. They hypothesized that two days of leg movement data is sufficient to accurately predict developmental disorders among the infants at risk. Smith et al. [27] developed an algorithm to measure the full day of leg activity and attempted to identify the relationship between the number of leg movements and the onset of walking. However, their test produced surprisingly unexplainable results as infants with a smaller number of leg movements began walking early than the babies with a greater number of leg movements.

VI. DISCUSSION

This section presents the various aspects of mobility-based assessment approaches and discusses their strengths and weaknesses.

A. *Mobility Parameters*

Analysis of mobility data is central to the identification of abnormal motor movements, which are characterized as developmental disorders. Identification of abnormal movements begins with the collection of mobility data using wearable sensor devices. The raw sensor data generated by these devices are preprocessed to eliminate noise and unwanted information. Furthermore, the sensor data will be cleaned and transformed, which will be consumed by the feature extraction phase. Features are selected in a way that represents motor movements that allow quantifying the intensity of abnormality. Table 3 lists the various mobility parameters chosen by the researcher in identifying the abnormal movements.

From Table 3, although the objective of each study is to quantify the limb, wrist, ankle, and head movements to identify the abnormal movements, all the researchers have not used the same set of features. For instance, studies [12] and [28] have employed accelerometer-based sensors and extracted the duration of each ankle movement, peak, and average acceleration of a movement. On the other hand, a researcher in a study [6] has measured the maximum and

Table 3: Summary of mobility parameters

Reference	Mobility parameters	Purpose of assessment	Type of movements
[6]	Maximum and minimum of the upper and lower body, maximum of all limbs, Pearson correlation between left and right leg	Predict abnormal motor function	wrist, ankles, and head movements
[7,30]	Skewness, cross-correlation, Area out of standard deviation of moving average and area differing from moving average, periodicity, the Detection rate	Diagnose CP	Ankle and wrist movements
[12, 28]	Duration of a movement, peak acceleration, and average acceleration during a movement.	Diagnose ASD, Classify TD & AR	Left and right ankle movements
[23]	Task completion time, Mean value of movement intensity, movement intensity variation, dominant frequency, smoothness of movements, average rotation energy, range of angular velocity, synchrony of arm movements	Predict motor disability	Movement data from predefined tasks
[25]	Fidgety movements (FMs) and general movements (GMs)	Diagnose CP	wrist, ankles, and head movements
[26]	movement count, movement duration, average acceleration, and peak acceleration	Classify TD & AR	Left and right ankle movements
[27]	Acceleration and angular velocity	Quantify leg movements	Left and right ankle movements
[31]	Average leg movement rate, movement duration, average acceleration, peak acceleration	Minimum number of days required for diagnosis	Left and right ankle movements

minimum acceleration of body movements. However, most of the researchers utilized mobility data from the wrist and ankles. The duration of the movement is another common parameter utilized by most of the studies [7][12][28][30][31]. The motivation behind using duration as a feature is to quantify the difference between healthy and abnormal motor development. Children with developmental disorders perform lower-duration movements while healthy kids perform longer-duration movements. Unlike in other experiments, [23] did not extract the mobility features directly from the raw sensor data. Rather, subjects were asked to perform a set of predefined tasks, and then features are computed from the data recorded from those predefined actions and movements.

B. *Challenges in Data Collection*

Infant’s motor assessment using wearable sensors has been increasing over the last decade because of their miniature size and wearability. Also, sensors can be attached to any part of the body and have the ability to function in both a laboratory setting and a home environment. Nonetheless, unlike adults collecting data from kids is not as easy for several reasons. (1) Preparing an infant for data collection is challenging because they are fragile and require utmost care. If it is a lab environment, then room temperature must be adjusted to the comfort of the child [30]. Additionally, the parent must ensure essential daily routines, such as breastfeeding and diapering. So, the child is ready and performs desired spontaneous movements. (2) Children's behavior is unpredictable, so sensors can fall off or become loose, which can eventually add noise to the data stream. For this reason, in a clinical setting or home environment, either a parent or a caregiver must always be present to take care of the sensor positing during the data collection period [31][32]. (3) size and placement of the sensor are important to reduce the irritation to the child. The ongoing research shows that the average weight of each sensor ranges between 10 grams to 30 grams [12][24][25]. However, the sensor's positioning has limited choices as it needs to be placed on the arms and legs to measure the limb movements.

C. *Wear Time*

Although there is no evidence for precise sensor wear time required for accurate data analysis, numerous studies collect the data for more than one hour for an objective conclusion. As wearable technology is advancing, it is now possible that sensors can be placed in diversified products like leg warmers [12], which are comfortable for the infant. Hence, some scholars have embedded sensors in the form of socks, and wristwatches and were able to collect the data for 2 to 5 days. Nonetheless, according to the study conducted by Deng et al. [31], two days of sensor data of infants is sufficient to differentiate between typical and atypical movements pattern. Yet, further investigations are necessary to minimize the wear time.

D. Accuracy and Validation

Accuracy validation of an infant's motor assessment method is crucial for decision-making in clinical research. Irrespective of the methodology used for the assessment, it is essential to compare the results with ground truth to measure the accuracy of the model. Researchers are primarily depending on two types of accuracy validation approaches in the context of an infant's motor assessment. Each method differs by ground truth. (1) In this approach, the sensor data collection procedure is video recorded such that normal and abnormal movements are annotated by experts. This annotated data is used as ground truth to validate the accuracy [12][22][23][24][27]. Undoubtedly, it is one of the popular and fastest methods used in many studies. (2) Alternatively, some investigators follow up on the infant's health status after a few months to validate their inference of those who were classified as high risk. In a study [20], the authors assessed children's movement complexity patterns at 3,6, 9, and 12 months of age, however, follow-up was done at 18 and 36 months of age to validate their results.

E. Noise Elimination

Unfortunately, infant movement data recorded from the sensors is mostly accompanied by noise [27]. Especially, in the context of infants, the amount of noise induced might be higher than normal. Because the daily routine of every child frequently changes between sleep, waking, and active states. Besides, a child might experience discomfort for unknown reasons. Then, either parent or caregiver must pacify the child to resume the data recording. Thus, the presence of noise is inevitable in children's movement data. Due to the effects of noise, movement assessment derived from the noisy sensor data is biased and inaccurate. To remove noise from the movement data, investigators have employed different techniques. To eliminate outliers, preprocessing and normalization of the data are some of the popular approaches [15][23][27]. In this approach, raw data is normalized and standardized to align within either first or third quantiles. Alternatively, parents or caregivers to write down the activity log of any major change in movement [12][22]. For instance, the activity log records the sleep, wake, and play times of the child. This method helps to extract the data, that is relevant and useful based on the activity log.

F. Quantifiable Parameters

Quantitative measurement has been used by several researchers for the automatic assessment of impaired motor function. In contrast, some researchers have developed a quantifiable metric that can measure the level of motor impairment. Their main objective is to quantify the variability and repeatability of arm and leg movements as a unit that can be used to measure the degree of neuromotor control. An objective metric called Motion Complexity (MC) [28] was proposed for full-day mobility data acquired from the sensors attached to both legs. MC is computed from the duration of movement, peak acceleration, and average acceleration during a movement. MC is essentially a measure of the variability of the recorded leg movements. Their experimental results demonstrate that two kids from the sample of five subjects have lower MC scores than the other three kids and that they later developed ASD. Sample Entropy (SampEn) is another quantitative measure introduced in [22]. The researchers postulated that AR infants' SampEn values are significantly lesser than TD infants. Hence, SampEn may be a potential early marker to detect abnormal growth of neuromotor control. Hoyt et al. [24] computed two metrics from the sensor data of upper limb movements: Use Ratio (UR) and mono arm use index (MAUI). These two components measure the asymmetry between the two arms. They postulated that infants with neurodevelopmental deficits might not use both arms like normal children. Their study results corroborated their theory.

G. Spontaneous Movements vs Therapeutic Movements

While spontaneous movements are either leg or arm movements recorded during an infant's active playtime, therapeutic (pre-defined) movements are designed by researchers in collaboration with clinical expert physicians [23]. Pre-defined movements are straightforward to process because they are logged in a well-controlled lab environment and accurate movement is well known in advance. Whereas spontaneous movements require additional processing to extract useful features as well as suppress unnecessary noisy data [27][30]. Although the pre-defined movement processing technique is simple to use, scholars are mostly interested in spontaneous physical movements. Because the treatment of spontaneous arm and leg movements is more practical and accurate.

H. Upper vs Lower limb movements

For a typical human being, the upper limbs are most important for performing daily routine activities such as self-care and work. Conversely, it is always not true for infants because most of their daily routine is taken care of by their parents or caregivers. Thus, which limb movements are feasible for quantifying abnormal movements is a debatable question. In fact, unraveling the answer to this question also depends on another question, i.e., which limb movements are convenient to collect the mobility data to identify the disability. Table 2 clearly shows that most of the studies used sensors for either the upper limb or lower limb. However, the majority of the researchers were interested in recording the mobility data only from lower limbs [12][22][26][27][28][29][31]. Although they did not mention the specific reason for their decision to use only lower limbs, it might be more convenient than attaching the sensors to the upper limbs.

I. Variations in motor movement skills

Motor behavior of a growing child generally includes actions of every part of the body from head to toe. Although the development of fine motor skills is critical, they are usually established during the first 2 years of a child. At each developmental milestone [33], a child reaches a particular stage. For instance, most babies can sit at the age of 6-8 months without any support. The absence of such crucial milestones eventually turns into a developmental disorder. Impairment in the growth of motor skills hampers various aspects of daily life including eating and self-care. Abnormality in motor abilities reflects the onset of a developmental disorder such as Autism. Variation in motor movements is the early sign of identifying developmental disability [21]. As described in Background section III, a child can be categorized into one of the three stages: Typically Developing (TD), At-Risk (AR), and Neurodevelopmental Disorder (NDD). A TD infant is considered to be healthy and therefore demonstrates a full repertoire of movement skills. Their movements are variable and complex in nature. They perform a wide range of movements from head to toe. On the other hand, an AR kid is on the fence about moving towards the disability stage. Though they may not exhibit complete abnormality in their movements, by careful observation and assessment certain impaired movements can be noticeable. There may be rigidness and inactiveness in limb movements. Their hand and leg motion might be cramped. In such a scenario, it is critical to diagnose the disorder as early as possible in order to facilitate early therapeutic intervention. A child who has already been diagnosed with a specific disorder is treated as NDD. The movements of NDD children are less complex and monotonous. Their actions contain repetitive and stereotypical movements. Compared to TD and AR, NDD child's movement acceleration is very low. In summary, variations in motor skills are the best predictors to identify the developmental disorder during early infancy.

VII. FUTURE DIRECTIONS

After careful deliberations based on recent literature, some of the most promising future directions are outlined below.

- *Reduced complexity and increased computational power:* The wearability and affordability of sensing instruments eliminate the complexity of using expensive equipment such as video camera systems to record the mobility data. However, it is still required to minimize the complexity involved in handling wearable devices, especially for newborn babies and toddlers. Future devices should be so tiny as not to create any discomfort for the babies. For example, if a monitoring device is designed as a thin patch that can be attached to a child's clothing or socks, it would be even more comfortable than existing sensor devices. Hence, it is essential to consider the design of sensor devices for babies and toddlers while increasing their computational power.
- *Long-term Data collection:* Most of the studies conducted by the researchers have focused on the assessment of the data recorded over a short duration. The majority of the studies collected mobility data for 8 to 13 hours (Table 2) and occasionally some researchers have monitored the data for 2 to 7 days. Nevertheless, a few hours of mobility data are not sufficient for accurate decision-making. Moreover, the likelihood of results being biased towards a particular day would be higher in the case of short-duration data collection. For example, a child may be more active some days than others. therefore, to reduce such a bias, it is essential to include data over an extended duration. In addition to this, treatment progress monitoring is another crucial factor in intervention therapy. Therapy may continue for days and sometimes even for months. Thus, it is important to design sensing equipment in such a way that it can collect mobility data for an extended period without human intervention.
- *Extended battery life:* All wearable sensors indeed operate on minimal battery life. But, in the event of long-term data collection, it is not optimal to remove the device frequently to recharge it. This frequent change would add unnecessary noise to the data and often disturbs the child. Therefore, sensors designed for infants should be able to withstand a long duration without charging.
- *Sophisticated techniques to eliminate the noise:* The mobility data collected from infants consists of a huge amount of noise due to the infant's daily routine. Soothing a crying child, feeding, and diapering are some of the common and repetitive tasks performed by either patients or caregivers. Since these tasks appear more frequently in the collected dataset, they generate enormous noise. State-of-the-art noise processing methodologies are human-driven, and they must be carefully removed by programmers. The presence of noise in the dataset may produce either biased or incorrect results. Hence, there is an immediate need for sophisticated automated methods to detect and suppress noise in mobility data collected from children.

VIII. CONCLUSION

Developmental disorders such as autism, hinder a child's typical behavior. As a result, they do not grow up like a normal child. Thus, it is crucial to diagnose and start treatment as early as possible in early childhood. However, the most frequently used clinical methods are subjective and based on the judgment of an observer. Furthermore, infants are required to visit the laboratories frequently. Therefore, observer dependency makes the decision ineffective in the early detection of the disorder. Quantitative measurement of disability using smart wearable devices accelerates the diagnosing process. Wearable devices are sophisticated for monitoring the mobility data of infants. Quantitative methods using wearable sensors facilitate objective measurement of the disability. Wearable instruments are tiny, affordable, and suitable for kids to record mobility data unobtrusively. Quantitative diagnosis can be performed by collecting mobility data from children. This paper highlights the importance of mobility-based quantitative prognosis and presented the various diagnostic approaches that are explored by the scientific community as a method of identifying the disorder by employing sensor devices. In addition, it explains various mobility parameters that have been explored by the researchers while developing the techniques to identify the developmental disorder. Finally, promising research directions on which future research should focus were also presented.

REFERENCES

[1] R.K. Thelagathoti and H.H. Ali, “On Exploring the Use of Mobility Parameters in the Analysis of Early Childhood Developmental Disorders”, 15th International Conference on Sensor Technologies and Applications, pp. 15–21, 2021.

[2] World Health Organization. “The Global Burden of Disease: 2004 Update. Geneva: World Health Organization Press”, 2008, [Online; retrieved: May 2022]. Available from: http://www.who.int/healthinfo/global_burden_disease/GBD_report_2004update_part3.pdf.

[3] K. A. I. Evensen, S. Sellæg, A.-C. Stræte, A. E. Hansen, and I. Meisingset, “Profile of children referred to primary health care physiotherapy: a longitudinal observational study in norway,” BMC Health Services Research, vol. 21, no. 1, pp. 1–10, 2021

[4] Centers for Disease Control and Prevention, “Developmental disabilities,” 2022, [Online; retrieved: May 2022]. Available from: https://www.cdc.gov/ncbddd/developmentaldisabilities/index.html

[5] B. Zablotsky et al., “Prevalence and trends of developmental disabilities among children in the united states: 2009–2017,” Pediatrics, vol. 144, no. 4, 2019.

[6] D. Gravem et al., “Assessment of infant movement with a compact wireless accelerometer system,” Journal of Medical Devices, vol. 6, no. 2, 2012.

[7] L.Meinecke et al., “Movement analysis in the early detection of newborns at risk for developing spasticity due to infantile cerebral palsy,” Human movement science, vol. 25, no. 2, pp. 125–144, 2006.

[8] J. Case-Smith, “A validity study of the posture and fine motor assessment of infants”. The American journal of occupational therapy: official publication of the American Occupational Therapy Association, 46(7), 597–605, 1992.

[9] M. C. Piper, L. E. Pinnell, J. Darrah, T. Maguire, and P. J. Byrne, “Construction and validation of the alberta infant motor scale (aims).” Canadian journal of public health= Revue canadienne de sante publique, vol. 83, pp. S46–50, 1992.

[10] C. Einspieler and H. F. Prechtl, “Prechtl’s assessment of general movements: a diagnostic tool for the functional assessment of the young nervous system,” Mental retardation and developmental disabilities research reviews, vol. 11, no. 1, pp. 61–67, 2005.

[11] F.Ferrari et al., “Cramped synchronized general movements in preterm infants as an early marker for cerebral palsy,” Archives of pediatrics & adolescent medicine, vol. 156, no. 5, pp. 460– 467, 2002.

[12] M. S. Abrishami et al., “Identification of developmental delay in infants using wearable sensors: Full-day leg movement statistical feature analysis,” IEEE journal of translational engineering in health and medicine, vol. 7, pp. 1–7, 2019.

[13] I. Braito et al.,“Assessment of upper limb use in children with typical development and neurodevelopmental disorders by inertial sensors: a systematic review,” Journal of neuroengineering and rehabilitation, vol. 15, no. 1, pp. 1–18, 2018.

[14] J. K. Poon, A. C. Larosa, G. S. Pai, “Developmental delay: timely identification and assessment”, Indian pediatrics, 47(5), 415-422, 2010.

[15] K. R. Heineman, A. F. Bos, and M. Hadders-Algra, “The infant motor profile: a standardized and qualitative method to assess motor behaviour in infancy,” Developmental Medicine & Child Neurology, vol. 50, no. 4, pp. 275–282, 2008.

[16] M. Randall, C. Imms, and L. Carey, “Establishing validity of a modified melbourne assessment for children ages 2 to 4 years,” American Journal of Occupational Therapy, vol. 62, no. 4, pp. 373–383, 2008.

[17] N. Bayley, G. Reuner. “Bayley scales of infant development”, (pp. 1-178). New York: Psychological Corporation, 1969

[18] Y. R. Burns, R.M. Ensbey, and M.A. Norrie, “The Neuro-sensory motor developmental assessment part 1: development and administration of the test”, Australian Journal of Physiotherapy, vol. 35, no. 3, pp. 141-149, 1989.

[19] S.K. Campbell, T.H. Kolobe, E.T. Osten, M. Lenke, and G.L. Girolami, “Construct validity of the test of infant motor performance”, Physical Therapy, vol. 75, no. 7, pp. 585-596, 1995.

[20] H. Chen, M. Xue, Z. Mei, S. Bambang Oetomo, and W. Chen, “A review of wearable sensor systems for monitoring body movements of neonates,” Sensors, vol. 16, no. 12, p. 2134, 2016.

[21] D. Campolo et al., “A novel technological approach towards the early diagnosis of neurodevelopmental disorders,” 30th Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE, pp. 4875–4878, 2008.

[22] B. A. Smith, D. L. Vanderbilt, B. Applequist, and A. Kyvelidou,“Sample entropy identifies differences in spontaneous leg movement behavior between infants with typical development and infants at risk of developmental delay,” Technologies, vol. 5, no. 3, p. 55, 2017.

[23] C. Strohrmann et al., “Monitoring motor capacity changes of children during rehabilitation using body-worn sensors,” Journal of neuroengineering and rehabilitation, vol. 10, no. 1, pp. 1–16, 2013.

[24] C. R. Hoyt et al.,“Using accelerometry for measurement of motor behavior in children: Relationship of real-world movement to standardized evaluation,” Research in developmental disabilities, vol. 96, p. 103546, 2020.

[25] C. B. Redd, L. A. Barber, R. N. Boyd, M. Varnfield, and M. K.Karunanithi, “Development of a wearable sensor network for quantification of infant general movements for the diagnosis of cerebral palsy,” 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC). IEEE, pp. 7134–7139, 2019

[26] D. Goodfellow et al., “Predicting infant motor development status using day long movement data from wearable sensors,” arXiv preprint arXiv:1807.02617, 2018.

[27] B. A. Smith, I. A. Trujillo-Priego, C. J. Lane, J. M. Finley, and F. B. Horak, “Daily quantity of infant leg movement: wearable sensor algorithm and relationship to walking onset,” Sensors, vol. 15, no. 8, pp. 19 006–19 020, 2015.

[28] R. B. Wilson, S. Vangala, D. Elashoff, T. Safari, and B. A. Smith, “Using wearable sensor technology to measure motion complexity in infants at high familial risk for autism spectrum disorder,” Sensors, vol. 21, no. 2, p. 616, 2021.

[29] S. M. McKay and R. M. Angulo-Barroso, “Longitudinal assessment of leg motor activity and sleep patterns in infants with and without down syndrome,” Infant Behavior and Development, vol. 29, no. 2, pp. 153–168, 2006.

[30] F. Heinze et al., “Movement analysis by accelerometry of newborns and infants for the early detection of movement disorders due to infantile cerebral palsy,” Medical &

biological engineering & computing, vol. 48, no. 8, pp. 765–772, 2010.

[31] W. Deng, I. A. Trujillo-Priego, and B. A. Smith, "How many days are necessary to represent an infant's typical daily leg movement behavior using wearable sensors?" Physical therapy, vol. 99, no. 6, pp. 730–738, 2019.

[32] N. Jalloul, "Wearable sensors for the monitoring of movement disorders," Biomedical journal, vol. 41, no. 4, pp. 249–253, 2018

[33] B.R. Carruth, P.J. Ziegler, A. Gordon, and K. Hendricks, "Developmental milestones and self-feeding behaviors in infants and toddlers", Journal of the American Dietetic Association, vol. 104, pp. 51-56. 2004.