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Towards a Deep Learning based Approach for an Infant Medical Analysis-A Review

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***Abstract*—Motion analysis is one of the known ways used to establish whether an infant is normal or abnormal. Studies have indicated that there is a clear difference in terms of speed or even time taken to respond to stimuli. General movements (GMs) are spontaneous movements of infants that involves the entire body differing in speed, amplitude and sequence. The assessment of GMs has helped in identifying infants that are at risk of neurological disorders. GMs assessment is based on videos recorded by parents or caregivers which are then rated by a clinicians or trained professionals. The General Assessment Tool has worked well, however, it is time consuming and very expensive. Several techniques have been proposed to automate the General Movement assessment tool which include marker-based techniques and markerless techniques. In our review we have systematically discussed the design features and technologies involved in both of them and identified both the strength and weakness. Thereafter, we explain the reasons for their limited practical performance. We conclude by proposing a deep learning approach that can be used to possibly address the issues raised in the existing techniques.**

***Index Terms*—Deep learning, General movement assessment, marker-based, markerless, infant**

I. Introduction

Motor disorders in children are very common and it's very difficult for parents to realize or discover them. In order to manage them fully, correct diagnosis is essential. Usually the nervous system malfunctions causing involuntary or uncontrolled movements or actions of the body. Most motor disorders range from seizure events to severe movement disorders. Common motor disorders include chorea – irregular movements (dance like), tremor- rhythmic shaking, myoclonus-movements involving quick, sudden, involuntary muscles jerks that cannot be suppressed, Dystonia- group of muscles contracts abnormally, tic disorders-involuntary movements of or sounds among many others. Early detection of motor disorders leads to early treatment and monitoring. Poor coordination of motors skills in children is associated with different neurological disorders such as cerebral palsy (CP), autism, epilepsy etc., hence if early diagnosed then proper therapies and medication can follow. In the past Pediatricians have received reports from parents on weird movements that their children show. They use these reports to diagnose the disorders and sometimes they get it wrong. The general movement assessment was developed on the basis of the discovery that the quality of the spontaneous movements made by young infants provides insight into the condition of their nervous systems. GMA is used by experts to determine different neurological conditions. But GMA suffers from human variability and again some symptoms come and disappear or even different disorders manifests themselves in a variety of symptoms.

Approaches from the field of deep learning have seen widespread use in recent years, particularly in the field of medical imaging for the purpose of determining the presence or absence of disease, as well as in other fields concerned with motion detection, such as sports. In this paper we present deep leaning approach to medical models' analysis of infant, in which a model will be able to predict the GMA class from infant motion sequence captured from characteristics of general body movements. Predicated results will help parents, caregivers or even Pediatricians detect the disorders early enough and therefore, the infant is subjected to early therapy, at the same time it will help in tracking down the progress of the infant as he or she goes through the therapy sessions to see whether there is some improvement or not.

II. Methodology

A. Data Sources and Search Strategies

The main aim for this paper was to review systematically the existing approaches that deal with classification of General Movements of infants which can be used in medical analysis for infants. We try to explore the methodology used by different authors and also explain successes as well as limitations. Our potential data source for articles were searched from PubMed, Science direct, IEEE and Google Scholar. The search criteria in the named data sources and databases were structured in a way that we could get papers that discussed about infants and movements and detection using machine learning, or computer based or image, and or motion sensors.

B. Study Selection Strategies

n our selection of review articles, we read through the abstracts of all the papers and excluded those papers that were not mentioning anything to do with general movements in infants and also focused much on the neurological problems. In light of this, we made it a point to ensure that the selected papers addressed the following topics: presentation of infant study, use of video or motion sensors, implementation of machine learning or any statistical approaches, and finally, the paper has to provide research on Infants in the relevant age range,focusing on both general and fidgety movements.

C. Study quality assessment strategies

We excluded all book chapters, magazines and any paper that was old, that is, any paper that does not fall between 2010 and 2021 unless it was a classical paper like the prechtl's papers. We settled on 120 papers. The next step was to exclude and remove duplicates. Subsequently, 40 papers were picked and after reading through all of them, researchers settled on the 26 that were used in this review.

III. General Movement Assessment (GMA)

General movements are a group of spontaneous movement patterns that are prevalent in the early lives of infants [26]. The movement patterns are spontaneous and happen without external stimuli such as caregivers or parents playing or talking to them. Infants have complicated motions that happen regularly and stay long enough to be seen. They entail whole body movement in a variable sequence of legs, arms, neck and trunk [26]. General movements (GMs) summarizes the motor behavior characteristics that are spontaneous in infants [30]. Variation and variability in human motor development are very key because they aid in evaluation of motor activities [10]. Variation means the availability and expression of a broad collection behaviors for a specific motor function, while variability implies the capacity to select from a collection of motor strategies that suits the situation [10]. General movements can be classified as normal or abnormal, [2]; [8]; [10]; [13]; [15]; [21]; [23]; [29]; [30]; [33]. Abnormal GMSs are categorized into: Poor repertoire GMs -defined by a repetitive sequence of movement components, speed, amplitude, and intensity that lacks, "ordinary variability, which seems stiff because it lacks the typical smoothness and fluency of character, occur when the limb and trunk muscles contract and release virtually simultaneously and look inflexible.; and Chaotic GMs defined as "movements that look jerky and abrupt due to their great amplitude and fast speed, [21].Prechtl introduced a method to predict cerebral palsy in newborns at high risk, the General Movements Assessment (GMA) [8]; [26]. This tool was used by clinicians to predict cerebral palsy in infants. Movements differ in speed, amplitude and sequence. The differences could help the clinicians to be able to predict the disorders in infants. GMs can be distinguished based on infants age for instance, preterm general movements, writhing movements and or fidgety movements [26]. General Movement Assessment (GMA) is a highly reliable diagnosis model. General Movements, derived from quality spontaneous movements, accurately reflect the state of the infant's nervous system. General Movement Assessment requires a highly trained medical practitioner to make sense of infant movements and predict if the infant is at risk of have disorders in future and the use of this tool has had excellent predictive value for cerebral palsy and other disorders. The assessment of GMs is quick, non-invasive, non-intrusive and easy to learn [7]. Absent, abnormal or sporadic general movements indicates risk of an infant having disorders while normal general movements predicts normal development [7]. Even having provided excellent results GMA tools has limitations. The approach is based on assessment of videos rated by trained and experienced professionals and hence, the method is time consuming and expensive [13]. Several studies have tried to automate GMA tool [13]. To automate the GMA, various techniques are used in detecting movement disorders such as cerebral palsy, autism, epilepsy based on the analysis of the body parts of an infant. These methods fall into two categories: those that rely on vision sensors and those that rely on motion sensors [16]. Though not common in the context of infants but widely successful among adults.

IV. Visual sensor-based approaches

Normally clinicians use videos recorded to study the general movements of infants to assess the disorders that the infant might be at risk with. To automate this procedure visual sensor-based approaches are used. This technique uses color images, depth information or both to analyze movements [16]. To track and detect human skeleton some methods use makers that are attached on human bodies to represent joint's locations which are used to provide motion information, whereas others exploit image features like colors, shape and edges to estimate joint's locations for movement analysis [19]. Visual based approaches either depends on markers attached on different parts of the body or use and explore the mark-less solutions to encode and and analyze the motion information. In the subsequent, the two specific methods are explained in greater element and evaluated with regard GMA

A. Marker-based Techniques

This method involves the placement of markers like infrared markers, reflective spheres, and light - emitting diodes at human body. This together with multiple cameras are used to provide information about the motion in human. [16] provides several studies in which different systems have been developed using markers. Human movement analysis commonly involves the use of markers placed on or near body joints. A review done on the evolution of marker based systems is presented in [6]. Use of markers-based techniques has yielded excellent results in human motion analysis; however, it has its own shortcomings. The use of markers is a cumbersome task because it requires calibrations, and again the complexity of tracking all markers attached to the body is a burden. Sometimes to yield good results one may require to increase the number of sensors on the body which is difficult especially to infants. Increasing the number of markers also may be a challenge especially when it comes to tracking because some of the markers may be occluded or even too close to each other. It is agreeable to a large extent that the markers can also make a patient uncomfortable and therefore, results might not just be accurate. Studies have been carried out on infants to assess general movements using marker-based systems. . Infants with cerebral palsy were the focus of one of the investigations. Utilizing a motion analysis technique, [22] created a way to gather 3D free-movement in newborn newborns using 20 reflecting markers and Seven infrared cameras. They extracted the recorded data,53 quantitative parameters that described the difference between the healthy and affected participant. Cluster analysis based on Euclidian distances was used to find the optimal combination of 8 parameters on which then classification is done utilizing quadratic discriminant analysis. The 3D motion analysis was done using Vicon 360 analysis system. The methodology presented a reliable discrimination between health and affected participant. The overall detection rate reached 73 percentage. However, the use of motion analysis tool is very expensive. Additionally, the set-up of the system is also challenging and very complex in terms of computation thus limiting clinical practicability. To aid in data collection and allow for precise measurement of joint rotation, [4] developed a technique to build and validate the specialized surface -marker cluster. Polycarbonate was used to create the marker holders. The material of choice is polycarbonate due to its indestructibility and the fact that it may be deformed plastically rather than shattering. g. Three or four sensors may be installed in a cluster frame. Since newborns don't have a lot of room, the thighs got the shorter (3 marker clusters) design while the shins got the longer (4 marker clusters). A Qualisys Motion capture system was used to record controlled movements on a soft body dummy doll and the data was compared to that obtained using two other methods: (i) optical tracking of makers placed anatomical landmarks and (ii) motion capture using inertial sensors. Although only a small number of healthy newborns were studied, the results revealed that the method may be used to comprehensively quantify infants' GM based on positional (direct read-out) and rotational information (estimation). The design also helps overcome the limitations that are normally associated with optical track of stand-alone markers in infants. However, this approach is still expensive, time consuming in terms of preparation. [14] used a computer-based analytic technique to look into how newborn limb motions correlate with the onset of cerebral palsy. They used digital cameras and reflective sensors, but only digital cameras captured the infant movements. Videos captured were between 1 to 5 minutes. They were digitized and pixel data for 2D positions of the reflective markers attached to arms and limbs were obtained. Examining a number of indices each captured different characteristics of spontaneous movements. They found out that higher jerkiness of spontaneous movement in infants is associated with later development of cerebral palsy. Nevertheless this approach has drawback in estimation of velocity in pixels/frame and also has issues with invariant to scaling, which can be addressed by use of depth camera [13].

B. Markerless Techniques

Several marker-free methods have been presented by various scholars in recent years, and these methods have gained widespread support as compared to markers techniques. Markerless systems utilizes various features of an image like shapes, edge and pixel locations to detect and track infant movements. Instead of using markers attached on the subjects or infants body parts, this approach uses digital video cameras placed above them, and therefore does not interfere or destruct with the movement. This approach, improves accuracy in estimating and recordings. Markerless approach was inspired by object recognition whereby, an object is divided into parts. For instance, [28] proposes a methodology which takes a single image input which is segmented into dense probabilistic body parts which are spatially localized near skeletal joints. Model based approaches aim at recovering human motion from one or more camera views and 3D model representations of human body [25]. Human motions can accurately be modeled by set of connected rigid segments. Multiple models have been developed by various researchers, with encouraging outcomes. [3] proposed Shape Completion and Animation of People (SCAPE) a statistical data model that learns from high quality scanned data. The model learns separate models of body deformation: one accounting for pose changes and another one accounting for differences in body shape between humans. Details like muscular deformations of the body in various stances are captured by combining the two parts to create a full dense body mesh. Both a body deformation model and a shape deformation model are included in this model. This model reduces the complexity of the mathematical formulation, enhances the effectiveness of the learning process, and enhances the capacity to identify models from data.But even so, this method has limited utility for infant's model analysis since it takes a collection of scans of a single person in different positions to understand the space of pose deformations. Unlike for adults, it is very difficult to instruct infants to take different position. This model is appropriate for adult pose estimation. [20] described a Skinned Mult-Person Linear (SMPL) Model which was an improved version of SCAPE that was proposed by [3].The suggested model's objective is to automatically learn a model of the body that is both realistic and transferable to different software engines. SMPL model is a skinned vertex-based model that accurately represents a variety of body shapes in natural pose. Just like SCAPE the parameters of the model are learned from data which includes pose templates, blend weights, pose-dependent blend shapes, identity-dependent blend shapes and a regressor from vertices to joint locations. A simple linear function is used to learn different pose and space and thus allowing the model to generalize arbitrary poses. This approach has the drawback of not being very effective with non-realistic animated characters, especially those with a vast variety of body parts or a small overall size, like newborns. In recent years, computer-based video analysis has emerged as one of the most effective markerless approaches. The use of RGB cameras that are placed above the subject to record spontaneous movements of infant without interfering with them would produce better result than the markers technique. The videos recorded can then be trained using different deep learning approaches which can now be used to predict abnormal movements in infants. [1] explored the feasibility of using computer-based video analysis to study fidgety movements in infants. The primary goal was to investigate the viability of a computer-based analysis of newborn spontaneous movements for categorizing fidgety and non-fidgety motions. Researchers examined 82 newborns, both full-term and preterm, at low and high risk for cerebral palsy.They analyzed the infants' movement quality using a general Movement Tool (GMT) that included a visual representation of the infants motions. The variables were obtained by determining the amount by which pixels moved from one video frame to the next. The quantity of motion was given by the sum of all pixels that changed between the frames in the motion image divided by the total number of pixels in the image. The study found that the videos of infants lacking fidgety movements had a significant lower mean quantity compared to those with fidgety movement. Due to methodological flaws and a lack of sufficient participants, this study was unable to develop a clinically relevant instrument [24] proposed an alternative for GMA which used automatic video-based assessment of infant movements. In their study retrospective videos with clinical GMA outcomes were evaluated to meet the criteria for automatic analysis consisting of skin model for segmentation and large displacement optical flow for motion tracking. A GMA was performed to capture 3–5-minute videos that were used to characterize movement as normal (typical), or abnormal (atypical). [24] were the first to apply the skin model to obtain information only related to the infant. They developed a five-step model which included: motion estimation which was estimated based on pixel displacement between frames, an infant segmentation to remove background, feature extraction, feature selection that helped to reduce the number of features, and lastly classification. They used several classifiers i.e., logistic, logit boost, and random forest that were trained to differentiate between typical and atypical movements and Cerebral Palsy and non-CP. They achieved better result of 85.83 percentage which was better than the previous models, but this model had a limitation in the estimation of velocity in pixels/frame. This was due to unknown distance between the camera and the infant, since they had used old video datasets where it was not easy to convert the dimensions from pixels to other units of measurement. Their proposed method of prospective analysis involves the use of a three-dimensional depth camera.

V. Motion sensor based approaches

Wearable motion sensors such us accelerometers, magnetometers have been used to provide reliable data for assessment of movement disorders [16]. The sensor have been used to assess the changes in movement and has produced accurate results. Recently wearable sensors have been used in capturing and analyzing GMs of infants without the presence of clinicians. [11] proposed a system that used accelerometer to analyze abnormal movements of infant. The methodology achieved between 88 and 92 perc overall detection rate. Similarly [9] proposed a system that used lightweight accelerometers to detect abnormal patterns of physical activities in infants. The system attained between70 to 90 perc accuracy rate. Despite the achievement, this approach has several limitations. The approach requires subjects to wear several sensors on the body which may actually cause discomfort to infant hence affecting their natural movements.This approach is time consuming as well because it requires complex setup.

VI. Use of Deep Learning Approaches

Deep learning techniques have been established because of graphics processing units' rising computational capacity These approaches learn complex problems and through a trained neural network, it can be possible to predict the outcome of different problems. Deep learning approaches together with pose estimation has been used to extract and analyses features for prediction. The computer based infant movement assessment (CIMA) model published in [12] is a novel machine learning model for predicting ambulatory vs non ambulatory function. The purpose of this model was to enhance the ability to identify high-risk infants for cerebral palsy before they reached 5 months of age. The CIMA model first detects the movements by tracking motion of body parts (head, trunk, arms, and legs) in a video. . Later, the prediction model makes use of the extracted characteristics from the body trajectories, such as the frequencies, amplitudes, and covariances of the movements of various body components. The prediction model identifies 5 seconds periods in the video with CP. The result is then summarized to show the presence or absence of CP. In contrast with [24] and others who presented models for automated CP prediction based on the identification of abnormal GMS and absence of fidgety movements., [12] used videos that were recorded during fidgety movements period, thus, CIMA model had potentials to capture some features which are typical for fidgety movements. It can be stated that CIMA model has several challenges both clinical and methodological. The distance optical flow was not fully estimated thus additional manual annotation is required, and therefore, the vertical and horizontal coordinates of the pixels are not directly related to bio-mechanical features such as the joints centers position or body parts center of mass. The other concern is that the video they used to train the model were from standardized camera setup with static mounted camera which recommended that videos should be taken from handheld smartphones. Also, the model is created from 5 second period non-overlapping time periods and it's very unlikely that all the 5 second periods within a video recording contain movements associated with CP. This may affect the estimate percentage. Markerless approaches in general have yielded good results because of their setup and also use of machine learning approaches. However, they face several obstacles including lack of datasets and occlusions. Usually, datasets for adults are readily available unlike for infants because of privacy issues. The other challenges that arise from these approaches are the occlusion. Unlike adults, it's difficult to get videos from different views for infants because one cannot instruct them to take different poses. As a remedy, deep learning approaches have tried to provide solutions to this by lifting 2D videos in 3D videos and availability of depth cameras that has made it possible to compute pose and motion parameters from depth images. The deep learning approaches are non-intrusive and therefore, does not interfere with the subject hence appropriate for infant models.

A. Generative Adversarial Networks (GAN) in Medical Analysis

Generative models are a class of machine learning models that are able to generate newer instances of data. They differ from discriminative models that are meant to discriminate between data instances of different kinds. Generative adversarial networks (GANs) are an ingenious method of training a generative model by redefining it as a supervised learning task with two sub-models: the generator model that we train to produce new instances, and also the discriminator model that attempts to characterize instances as either real (from the domain) or fake (generated). Together, the two models are trained in an adversarial, zero-sum game until the discriminator model can be deceived roughly half the time, indicating that the generator model is producing credible samples. The medical area has also seen GAN applications, with [31] providing a comprehensive overview of the most up-to-date approaches for medical imaging analysis. Medical reconstruction, picture quality enhancement, segmentation, lesion identification, data modeling, and classification are just a few examples of the challenging tasks in medical image analysis that may be tackled with the help of GANs and their derivatives. To combat the lack of data in the person re-identification challenge, [32] employed a GAN-based model. Pictures with two perspectives (cross view photos) may be created from source images and skeleton images using a conditional GAN. After that, the resulting cross-view photos are sent into a discriminator, where they may be used to re-identify the original subject. [27] used GAN to speed up the creation of MRI images. GAN was utilized by the authors to produce missing k-space samples rather than MRI pictures from pre-existing MRI images. Tasks requiring an MRI scan but which are time-sensitive or high-resolution are suitable for their method. In order to test how successfully ehrGAN generated EHR as genuine samples, [5] employed two longitudinal real clinical datasets on heart failure and diabetes. The discriminator was designed using the framework of the standard prediction model [17]. The generator was modified for a semi-supervised learning scenario based on the variational contrastive divergence. Semi-supervised learning using ehrGAN was used to augment the data for better risk prediction, which led to better generalization and more accurate predictions [17]. When trying to determine if a patient has a rare disease, GAN was utilized by [18]. Using the IQVIA longitudinal prescription and medical claims database, we maximized and then added to the goal function of the discriminator, which was to correctly identify unlabeled data as actual data [17]. The semi-supervised learning framework for uncommon illness diagnosis increased prediction accuracy by 5 percentage compared to the baseline procedures (measured by precision-recall curves and area under the curve) [17].

VII. Conclusion

This paper present reviews on the recent approaches that have been used in medical infant analysis that have attempted to automate the general movements that would be used instead of the traditional GMA. Also, the paper highlighted in details the advantages and limitations of different approaches. It has been stated that sensors for motion are affordable and can produce good results when placed on infants' limbs which can be used to record different movements made by the infant. However, this procedure is cumbersome and needs an expert to handle. It is also time consuming as a lot of calibrations are needed.Too many markers are needed for more accurate results and this makes participants uncomfortable especially infants. Markerless techniques provide the freedom of using no markers hence very easy to set up and also do not make the infant uncomfortable. These approaches, however, has some shortcomings such as quantifying the amount of motion that could be used for classification of movement due to difficulties in the estimation of velocity in pixels/frame. This was due to unknown distance between the camera and the infant, since they had used old video datasets where it was not easy to convert the dimensions from pixels to other units of measurement. This approach also had a challenge of getting datasets. Deep learning approaches are proposed to improve on the current existing markerless techniques. Deep learning techniques take advantage of extensive learning of pose and shapes which is used to estimate the movements made.With deep learning approaches, the procedure for setting up experiment will not be as a cumbersome as that of markers techniques and and there will be no markers attached. With the above mentioned in mind, this research presents a comprehensive, end-to-end, deep learning-based system that includes the following:

- In order to successfully deploy learning-based techniques, it is required to collect a large dataset consisting of infants for GMA.;
- For the purpose of producing reliable findings, the dataset need to incorporate a variety of sensor modalities, such as visual and depth;
- The identities of those taking part in the activity have to be concealed by making use of the privacy protection strategies.
- The system should classify GM as normal or abnormal

The implementation of multi-task learning approach would be beneficial to track the movement of different limbs simultaneously. To analyze the work, researchers propose the use of generative adversarial network (GAN) deep learning approach, a model that follows an adversarial approach in which two deep model generators and discriminator compete with each other. This model will involve learning normal patterns and identifying any deviation as abnormal movement.

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