Detection of Spastic Cerebral Palsy Using Different Techniques in Infants

Nancy Sukhadia and Pariza Kamboj

Abstract Cerebral Palsy (CP) is a complicated neurological condition in infants. CP refers to brain injuries that affect different body parts. It must be detected in early childhood as early detection can help to improve outcomes through therapy-based interventions. Generally, pediatricians detect CP based on the physical movements of infants, but sometimes, it becomes difficult to detect this way at the early stages. The absence of "fidgety movement" is a strong predictor to detect CP using the combination of video and sensors. There are four kinds of cerebral palsy in which spastic cerebral palsy is very common in infants. It refers to muscles-related problems like muscle stiffness and muscle weakness. Spastic cerebral palsy is detected by measuring the angle between joints or other parameters like stride length, leg length, age, and cadence to name a few. Spastic cerebral palsy is typically detected using surface electromyography (sEMG), using sensors, namely accelerometer, inertial measurement unit (IMU), or using machine learning techniques. sEMG can be used only for recording the electrical activity of muscle tissues or visual representation. Impulsive extreme movements of lower and upper limbs are being observed using accelerometer, but it is not helpful to get postural information. Wearable IMU sensor consists of three sensors, namely accelerometer, gyroscope, and magnetometer. IMU records movement facts in three dimensions at numerous samples per second and forms any continuous hours without any mediation. This paper aims to study various conventional and modern techniques to examine CP and compares them based on various parameters. After a thorough study of various methods, it was found that IMU sensors provide the best way to detect CP in the case of infants as wireless IMU is a low cost, non-invasive, and easy to wear solution. They also provide 360° measurements through three sensors each on three axes which provides more accuracy in comparison with any other method.

N. Sukhadia (✉) · P. Kamboj
Sarvajanik College of Engineering and Technology, Surat, India
e-mail: nancysukhadia27@gmail.com

P. Kamboj
e-mail: parizakamboj@scet.ac.in

1 Introduction

The number of preterm children born in many industrialized countries has been increased tremendously. In India, 3,341,000 babies are born too soon each 12 months and 361,600 children underneath 5 years of age die due to direct premature complications [1]. Early infancy is an essential phase of an infant's existence, as many important major developmental mileposts are achieved progressively in the first six months which lay down the foundations for their imminent life [2]. However, these preterm infants are an expanded danger of growing illnesses like motor dysfunction, retinopathy, and apnea to say a few. Cerebral palsy (CP) is a prevalent motor dysfunction in preterm infants which is found in 4–20% of premature children based on their gestational age [3]. Neurodevelopment assessment in an infant is important to detect diseases at an early stage to save their life.

The word cerebral palsy is made up of two words cerebral and palsy. The initial one refers to the cerebrum, the uppermost area of the brain, and later one refers to the resultant disorder because of brain injury, which is shown in Fig. 1. The term "cerebral palsy" also refers as CP is a group of permanent cerebro-motor dysfunctions that appears in early infancy [4].

Cerebral palsy affects body movements and coordination permanently, but it is not degenerative. CP does not get worse over time, though the exact symptoms can change over a human's lifetime. Signs and symptoms of CP also vary among infants and overtime in cerebral palsy. Symptoms of cerebral palsy include poor coordination, oral problem, stiff muscles, weak muscles, paralysis, twisting movements, stormy movements, and tremors to mention a few of them.
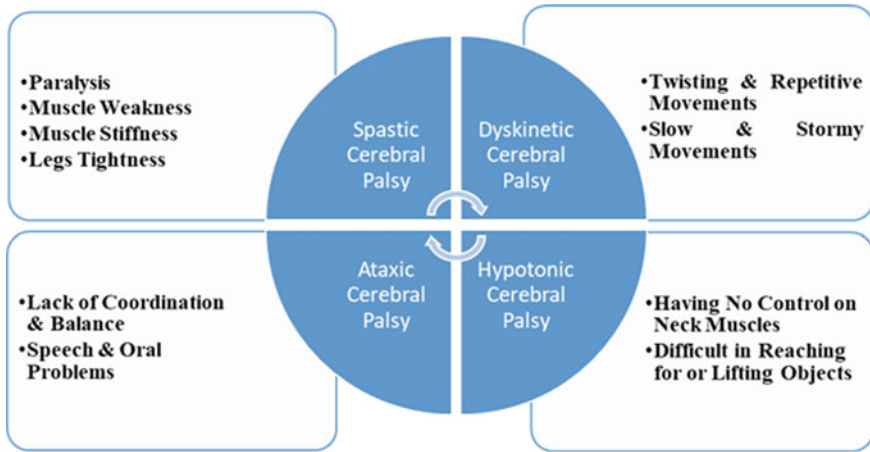
Fig. 1 Cerebral palsy [5–7]
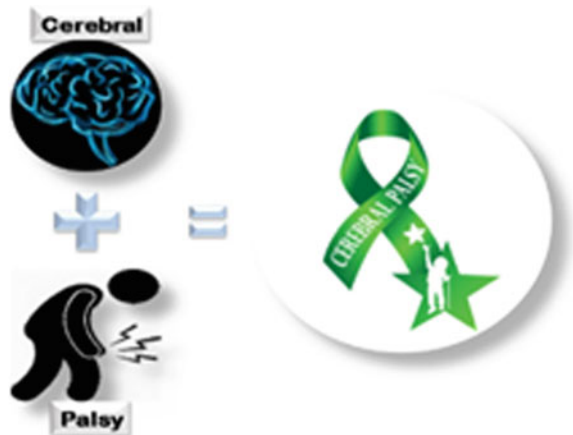
Fig. 2 Classification of cerebral palsy [8–11]

There are mainly four categories of cerebral palsy such as spastic, dyskinetic, hypotonic, and ataxic cerebral Fig. 2, due to which different symptoms are exhibited.

The organization of this paper is as mentioned: Sect. 2 discusses the spastic cerebral palsy. Section 3 discusses various techniques to examine spastic CP. Section 4 discusses the broader categories of available techniques. Section 5 concludes this study on CP.

2 Spastic Cerebral Palsy

Spastic CP is the predominant category in infants which is shown in Fig. 3. Infants with a spastic cerebral palsy struggle to eat, speak, and control their movements. Many infants with a spastic cerebral palsy walk with an abnormal gait, such as eating, speaking, and walking on their toes instead of flat feet. Symptoms of spastic cerebral palsy are as follows:

1. Stiff, tight muscles (hypertonia) on one or both sides of the body,
2. Problem of joint's extension,
3. Exaggerated movements,
4. Abnormal reflexes,
5. Limited mobility,
6. Walking on tiptoes,
7. Abnormal gait,
8. Crossed knees,
9. Contractures.

Fig. 3 Spastic cerebral
palsy [12]

Spasticity is the chief symptom in most infants suffering from cerebral palsy. It is explained as a motor dysfunction due to upper motor neuron syndrome (UMNS) causing an increase in tonic stretch reflexes. Cerebral palsy infants encounter various troubles such as difficult independent ambulation due to abnormal posture gait, and they also have a joint impairment and in extreme cases, pain, and tenderness. Spasticity of lower limbs typically accompanies clonus, involuntary muscular spasm involving repeated, often rhythmic, contractions and relaxations in muscles [13]. Treatment for spastic cerebral palsy varies with an individual case. The severity of signs, area of movement problems, and secondary situations are the biggest elements in charting treatment. However, there are few fundamental methods of treatment for CP which include physical therapies, speech therapies, occupational therapies, medications, and surgery.

3   Techniques to Examine Spastic Cerebral Palsy

Pediatricians measure the angle manually or using goniometer as shown in Figs. 4 and 5 that does not give accurate angles in infants to predict spastic cerebral palsy. The evaluation of spontaneous "general movements" is a key examination of cerebral palsy in children, i.e., locomotion made in lying down position on a flat surface while not surrounded by any things that inhibit movement or tempt mind [14]. Although general movements assessment (GMA) can predict cerebral palsy with excessive accuracy, it is not broadly followed clinically because pediatrician should be trained precisely in assessing movement patterns and individuals' judgments are subjective too.

Fig. 4 Manual examinations by pediatrician [1]

Fig. 5 Angle measurement using goniometer [24]

Pervasive attempts have been made to collect quantitative data regarding the angle of the limbs which is decisive information in detecting CP. With the technical development, clinicians easily do the documentation of the electromyography (EMG) and kinematics assessment of individuals. Gait patterns have also been analyzed to achieve quantitative information. Moreover, in recent years, gesture recognition using worn sensors has become famous due to extended processing ability on mobile gadgets and the increasing accessibility of software, complicated sensors, and algorithms [15].
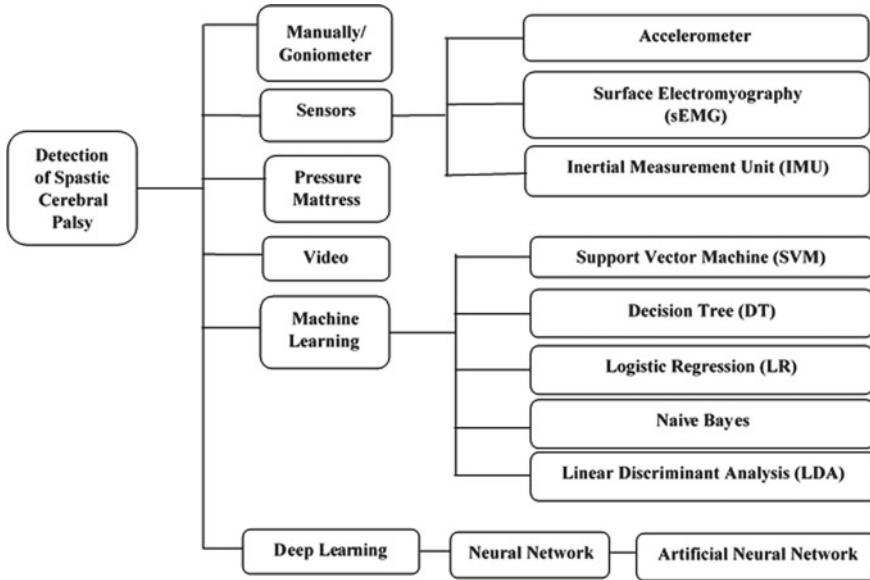
Fig. 6 Detection of spastic cerebral palsy using different techniques

In the past couple of years, many advance machine learning techniques have been developed to classify cerebral palsy infants and normal infants with high accuracy, for example, unsupervised learning methods like decision tree classifiers. Many of these strategies had been exploited in the clinical-related applications which include gait analysis. Out of many machine learning techniques, particularly support vector machine (SVM) and kernel Fisher discriminant (KFD) are known as high-performance classifiers, with the higher dimensional input dataset. In the era of technology, digital cameras and optoelectronic systems are also employed to detect abnormality of movement in infants. All such techniques to detect spastic CP in infants can be categorized in various categories as shown in Fig. 6.

During the last three months of fetus life, cerebral maturation happens rapidly. Cerebral maturation brings about continuous modification of muscle tone. For detecting cerebral palsy, the examination of postural reactions of muscle tone and reflexes is important [16]. Resting posture or attitude can be categorized into passive tone and active tone. The passive tone indicates the extensibility of a muscle when physicians apply positive actions to the infant at rest in a passive position so that the amplitude of passive kinesics of a single joint can be measured. On the contrary, the examination of an active situation in a child known as active tone, for instance, a pediatrician should place a child vertically in the righting reaction of the trunk as shown in Fig. 7.

Authors in [5] detect the lower limbs' assessment of the MTS improves the accuracy and reliability of the MTS itself. In this study, a control group of a total of thirty subjects including a CP group of twelve CP infants, a TD group of eight

Fig. 7 Righting reaction [17]

typically developed children, and an AD group of ten healthy adults were taken. Sixteen sEMG sensors have been gathered bilaterally from eight muscular tissues of the lower limb of the subjects for the duration of the ahead walk at a comfortable velocity. Surface electromyography signals of lower limb muscle tissue and acceleration records are compiled concurrently with the usage of a homemade multi-channel system consisting of sEMG sensors. Authors opine that greater than eight muscular tissues can be taken into consideration to enhance the accuracy of consequences for the prediction of cerebral palsy.

Movement estimation in infants has been done using a video/inertial measurement unit hybrid system [3]. Based on this movement estimation, a classification accuracy of 84% was achieved in the diagnosis of abnormal locomotion in infants using SVM. Twenty infants between the 2 and 4 months age were recruited for this hybrid system. The authors used five *Shimmer 3* sensors, attached on the left and right ankles, left and right wrist, and torso using soft wrist bands and ankle bands as shown in Fig. 8. Medical experts analyzed the fidgety and non-fidgety movements in infants by recording video. The results in detecting fidgety locomotion are giving good accuracy on a small dataset, but it needs to be confirmed on a large dataset too.

A combination of five IMUs along with two pressure mattresses has been used for the infant's arm motion and trunk posture assessments [2]. Firstly, this combination is applied to a human replica that has realistic anthropometric characteristics of newborns. A human replica fitted with five IMU bands, one on each upper arm, one on each forearm, and one on the torso is positioned on top of two pressure mattresses as shown in Fig. 9. After that, motor pattern parameters in a healthy child are acquired by keeping the baby on the pressure mattresses along with one torso, two forearms, and two upper arms IMU sensors to confirm the suitability of method and parameters. Using this setup, motor pattern parameters inaccuracy under ten percentage and kinematic estimation inaccuracy in a range of two centimeter are achieved. So an acceptable accuracy is achieved with a simple to use setup.

An IMU-based pose estimation method using prolonged Kalman filter and kinematic chain modeling is adapted in this approach [18]. IMU-based pose estimation has been used to analyze and reduce the sensitiveness to sensor placement and body span. This model is used for lower body (hip, knee, and ankle) pose estimation during
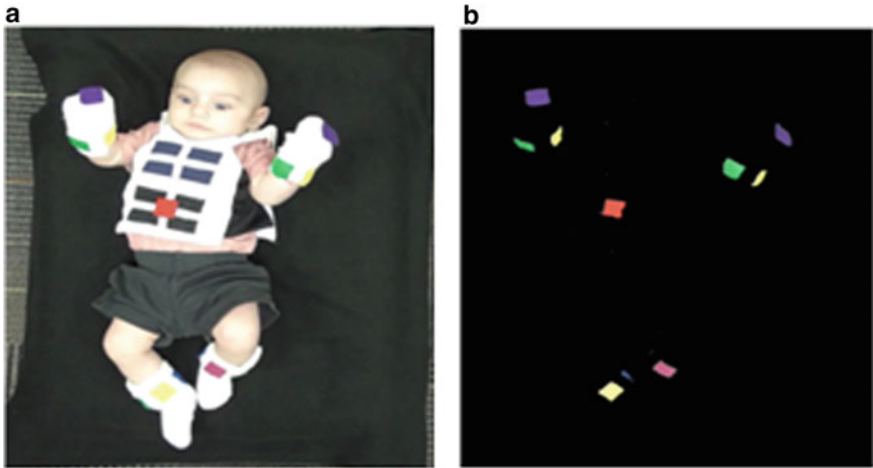
Fig. 8 **a** Infants with the shimmer sensors and color patches [3]. **b** Detection color plot [3]

Fig. 9 IMU sensors attached on upper limbs and trunk [2]
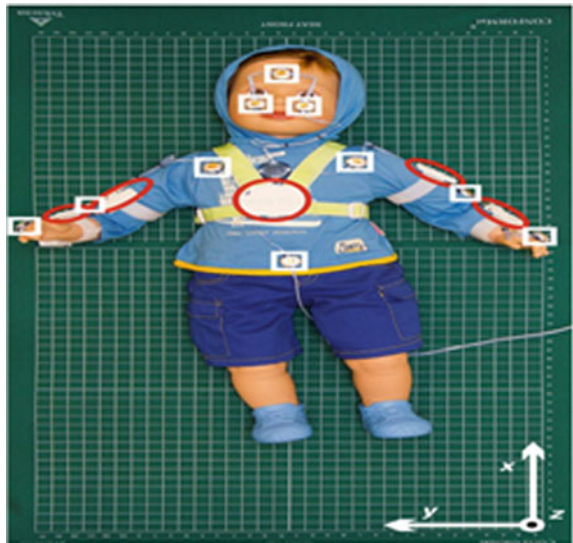
clinical movement tests such as the single-leg squat (SLS), and the sensitiveness to parameters in addition to the knee and ankle calibration is investigated. A simple calibration protocol figuring out the IMU orientation on the body can provide better posture estimation performance. The major benefit of this approach is that it provides a tri-axial estimation of the knee, ankle, and hip joints together.

Cerebral palsy is predicted by gesture recognition in infants [15]. These gestures, known as cramped-synchronized general movements (CSGM) especially correspond with a prognosis of CP. The authors recorded information from ten infants admitted
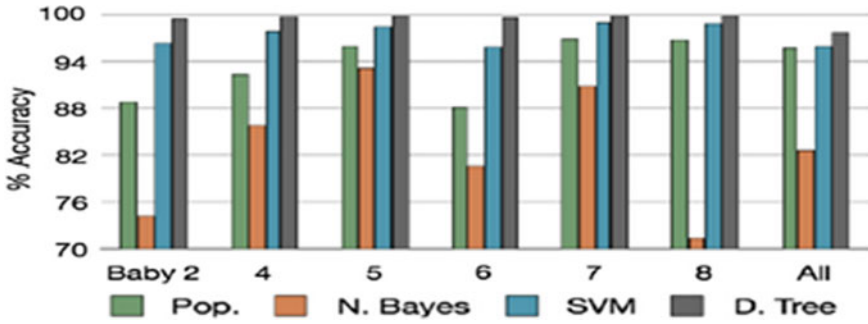
Fig. 10 Accuracy of different machine learning techniques [15]

to the new child extensive care unit at UCI Medical Center. In this method, five accelerometers are attached to an infant's upper limbs (two on the wrist) and lower limbs (two on ankle) and one on the trunk. Machine learning techniques, for instance, decision tree, SVM, Naive Bayes, and PCA, are applied on a dataset of ten infants. Results from this test exhibit that decision trees acquire the greatest accuracy of 99.46% among all the techniques tested succeeded by SVMs (90.46%). Naïve Bayes carried out worse (70.43%) as shown in Fig. 10.

Identification of gait (on foot manner of the individual) is essential for analysis in addition to for the right evaluation of the treatment consequences. Authors in [19] discover the utility of SVM for automated finding and classifying the CP based on two essential spatial gait parameters (stride duration and cadence) as input aspects. A total of 156 children dataset having 68 normal healthy infants and 88 with spastic diplegia from cerebral palsy children's dataset is used in the SVM method. The results of examination of a dataset using a tenfold cross-validation scheme revealed that an SVM classifier classified the infant groups with an accuracy of 83.33%. To get more certainty in the result, the gait parameters like an individual's lower limb length and age were added. The total dataset of 156 infants was divided into ten equal-sized segments in which six segments consist of 16 infants and the rest four segments consist of 15 infants. The accuracy of SVM results is higher than linear discriminant analysis (LDA) and a multi-layer perceptron (MLP) based classifier which is 3.21% and 1.93%, respectively. SVM kernel functions such as linear, polynomial, radial basis, and ANOVA spline were studied in this approach. Among these four functions, the polynomial and radial basis kernel performed better than the other two functions.

Many known classification methods have been carried out in numerous applications such as decision trees, Fisher's linear discriminant analysis (FLD), and artificial neural networks to name a few. Also, many methods have been used to examine the performance of pattern classification schemes. Generally, holdout, leave-one-out, and cross-validation methods are used for evaluation. Authors in [20] explore various classification paradigms in the cerebral palsy gait analysis. In this technique also, a dataset of 68 healthy infants and 88 infants with spastic diplegia is used with parameters such as stride length and cadence. The tenfold validation method along

with kernel Fisher discriminant analysis (KFD) for the classification of CP gait has been used in this approach too. Many different cross-validation consequences show that KFD offers better category accuracies than SVM and is advanced to a few other class methods consisting of the decision tree, multiple layer perceptron, and *k*-nearest neighbor.

Wearable sensors such as accelerometer, sEMG, and Opal to mention a few are used to evaluate an infant's limb moves the whole day. Authors in [5] used acceleration and angular momentum to evaluate infant-produced movements. Two accelerometers are attached to the infant's lower limb across 8.5 h, during which the child is taken care of by the nurse. Accelerometers are used in this study to track acceleration only and recording the leg movement. But in this approach, around fifteen percentage of child leg moves can be credited due to the background motion of the nurse. Table 1 provides a comparison among the various cerebral palsy detection techniques.

Table 1 Comparative analysis of various CP detection techniques

S. No.	Technique	Measurement	Pros	Cons
1	Manually/goniometer	Joint angle	Identify active and passive tone	No accuracy
2	Video	Limb movements	Detecting fidgety movement	Dependency for capturing video
3	Accelerometer	Limb movements	Recognize the gesture	Measures only horizontal and vertical orientation
4	sEMG	Limb movements	Easy to understand muscles abnormality Record single muscle activity	Only feasible for single muscle in an individual
5	Pressure mattress	Infants' activity level	Simplicity to use	No joint angle measurement
6	IMU (accelerometer + gyroscope)	Joint angle of both limbs (orientation and rotation both)	Accurate angle Low cost Non-invasive	Magnetic field cannot be measured
7	IMU (accelerometer + gyroscope + magnetometer)	Joint angle of both limbs (orientation, rotation, and magnetic field also)	Accurate angle Low cost Non-invasive Measures three-dimensional data on each of three-axis	–
8	Machine learning	Stride length, cadence, leg length, and age	More accurate results	Larger dataset is required

Another big research in cerebral palsy is done using multivariate analysis and machine learning techniques. Multivariate analysis is useful for the prediction of cerebral palsy and machine learning approaches made it viable to automatically identify movement impairments in high-risk infants. It is anticipated that multivariate analysis and machine learning will play a massive role in improving the investigation and remedy of cerebral palsy to diminish fatality and morbidity rates and enhancing patient care for infants with CP [6]. The multivariate analysis includes statistical techniques, for instance, principal component analysis (PCA), canonical variate analysis, independent components analysis, and multivariate regression.

Researchers have used different sensors such as accelerometer, sEMG, pressure mattress, and IMU. These sensors are typically attached to upper limbs and trunk to measure the angle of joints. In some literature work, machine learning techniques, such as SVM, decision trees, and principal component analysis based on four parameters: (i) stride length, (ii) cadence, (iii) leg length, and (iv) age, are also used to predict or classify CP in infants. All these techniques individually have their specific limitations such as the machine learning technique needed more data for accuracy. A combination of sensor-based and machine learning techniques overcomes these limitations and provides a better accuracy to detect/classify CP in infants.

4 Discussion

In the area of neurodevelopment related to the detection of cerebral palsy, big tries had been made to gather quantitative information about the angle of the limbs which is decisive information. Pediatricians measure the angle manually or using goniometer as shown in Figs. 4 and 5. Sometimes pediatricians could not measure the angle accurately in an infant which might lead to the wrong detection of CP. Nowadays, cerebral palsy is detected using different techniques such as sensor-based, machine learning, and video-based approaches employing specific parameters as mentioned in Table 2. These techniques provide much better accuracy in comparison with the conventional

Table 2 Parameters used in various techniques to detect cerebral palsy in infants

Techniques	Parameters to detect/classify CP
Sensor-based 1. Accelerometer 2. sEMG 3. IMU	1. Angle between joints of upper and lower limbs
	2. Movements of the infant
Machine learning	1. Stride length
	2. Cadence
	3. Leg length
	4. Age
Video-based	1. Movement of the infant's upper and lower limbs

measurement method by goniometer. Using the sensor-based techniques, pediatricians can measure the angle between joints of the upper limbs, lower limbs, and trunk accurately. Sensors such as Opal, accelerometer, sEMG, and IMU to name a few are used to measure the angle between joints that provide the 3D image of the limbs. By this image, a pediatrician can predict the CP early in infants.

Existing motor evaluation techniques like digital cameras and optoelectronic systems are afflicted by material occlusion and require complicated setups [3]. Electromyography (EMG) can be used only for recording the electrical activity of muscle tissue or visual representation. Some sensors like accelerometer, sEMG, and IMU are very useful for neurodevelopment assessment [21]. Wearable sensors like accelerometer have turn out to be increasingly famous as a measurement of movement aspects and physical actions. Accelerometers have been used to observe neonate's continuous upper and lower extremities moves however do not offer postural facts. To overcome these drawbacks, multi-sensor measurement systems provide a better alternative to detect the motor fidgety movement. IMU sensor as shown in Fig. 11 is the combination of three sensors, namely accelerometer, gyroscope, and magnetometer which is shown in Fig. 12. From the survey carried out, we found that the IMU sensor gives a more accurate angle between joints as compared to other sensors because it measures orientation, rotation, as well as the magnetic field.

Fig. 11 IMU sensor [22]

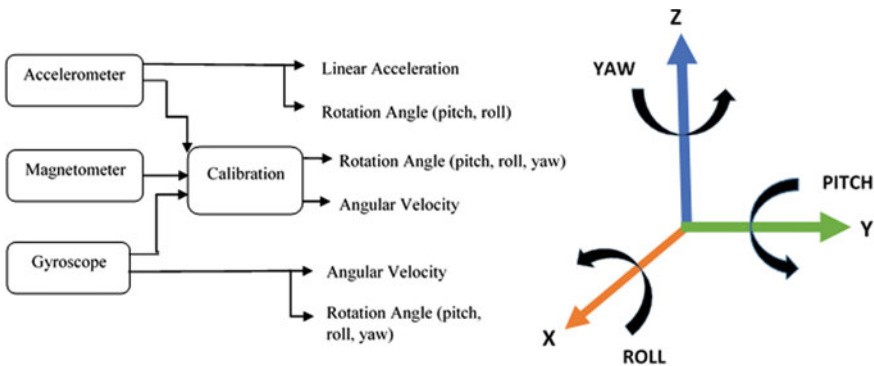**Fig. 12** IMU comprising of three types of sensors and working principal [21]

4.1 Accelerometer

An accelerometer is an electromechanical tool used to measure acceleration forces [23]. An accelerometer measures the movements of the limb and quantifies them such that each break or modification is counted as a new movement.

4.2 Surface Electromyography (sEMG)

Electromyography (EMG) can be used only for recording the electrical activity of muscle tissue or visual representation. sEMG assesses muscle function by recording muscle activity from the surface above the muscle on the skin [24]. As such, sEMG is the analytic device that is used in a broad spectrum that assesses muscular coordination in cerebral palsy.

4.3 Inertial Measurement Unit (IMU)

Wireless IMUs shown in Fig. 11 are low cost, non-invasive, and easy to wear. This sensor is the combination of a tri-axial gyroscope, a tri-axial magnetometer, and a tri-axial accelerometer [25]. IMU measures the angle of joints and movements when an infant moves his/her limbs. It can measure movement throughout 360° using three sensors each on three axes and hence used to analyze infants' spontaneous upper and lower extremity movements. There are three types of rotation angles: pitch [rotations of the y-axis ($\pm90°$)], roll [rotation of the x-axis ($\pm180°$)], and yaw (rotation of the z-axis ($\pm180°$)] as shown in Fig. 12.

The benefit of the usage of IMU is that it will no longer be interfered with by using the external magnetic area across the sensor while used near the ferromagnetic material. Using a combination of accelerometer and gyroscope handiest, it may not be enough to increase the accuracy of the measurement because of sensors' noise and the gyros drift problems. So magnetometer measures the magnetic field when a force is applied [21].

IMU sensor is used in many fields such as augmented reality, health care, drone, navigation system, and robotics. For example, an IMU having only a gyroscope and an accelerometer was used in a device to study the movements of the post-traumatic patients [21]. This IMU records a three-axis accelerometer and/or three-axis gyroscope data at many samples per second, permitting to file movement records unobtrusively across many continuous hours without any intervention.

4.4 Machine Learning

Many machine learning algorithms such as SVM, decision tree, and PCA have been applied for detecting CP based on infants' limb movements [15]. Machine learning techniques have been applied only for the classification of healthy infants and CP infants. But none of these techniques has been used for predicting cerebral palsy in infants at early stages so far. Four parameters (1) stride length, (2) rhythm, (3) lower limb length, and (4) age are taken in machine learning techniques to classify the CP infants and healthy infants.

4.5 Hybrid System (Video and IMU)

Some authors also have used a video and the IMU hybrid system for assessment of the infant's movement. In this hybrid system, IMU sensors are attached to infants' limbs. After that, Infants' movements are recorded in a video. From the video recording, pediatrician can classify the healthy infants and CP infants easily based on the abnormal movements. Cramped-synchronized general movements (CSGMs-abnormalities) identified by a trained specialist from the video have been correlated with CP.

5   Conclusion

The diagnosis of cerebral palsy using a machine learning technique is more preferable. Parameters such as age, stride length, leg length, and cadence are used in machine learning techniques to detect cerebral palsy in an infant. The IMU-based technique is very useful to detect cerebral palsy in infants at early stages. No research has been done on the IMU-based technique applying on all the limbs. IMU sensor can be used on the trunk, upper limbs, as well as lower limbs for measuring angles between arms, ankle, and other joints. Thereafter, a machine learning model can be developed based on the measurements taken using IMU to detect whether the infants are suffering from cerebral palsy or not. Based on the outcomes, the model can be validated against the diagnosis which is done by the pediatricians. This study concludes that the IMU sensor gives better accuracy for angle measurement.

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