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Review article

Optimal locations and computational frameworks of FSR and IMU sensors for measuring gait abnormalities

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ABSTRACT

Neuromuscular diseases cause abnormal joint movements and drastically alter gait patterns in patients. The analysis of abnormal gait patterns can provide clinicians with an in-depth insight into implementing appropriate rehabilitation therapies. Wearable sensors are used to measure the gait patterns of neuromuscular patients due to their non-invasive and cost-efficient characteristics. FSR and IMU sensors are the most popular and efficient options. When assessing abnormal gait patterns, it is important to determine the optimal locations of FSRs and IMUs on the human body, along with their computational framework. The gait abnormalities of different types and the gait analysis systems based on IMUs and FSRs have therefore been investigated. After studying a variety of research articles, the optimal locations of the FSR and IMU sensors were determined by analysing the main pressure points under the feet and prime anatomical locations on the human body. A total of seven locations (the big toe, heel, first, third, and fifth metatarsals, as well as two close to the medial arch) can be used to measure gate cycles for normal and flat feet. It has been found that IMU sensors can be placed in four standard anatomical locations (the feet, shank, thigh, and pelvis). A section on computational analysis is included to illustrate how data from the FSR and IMU sensors are processed. Sensor data is typically sampled at 100 Hz, and wireless systems use a range of microcontrollers to capture and transmit the signals. The findings reported in this article are expected to help develop efficient and cost-effective gait analysis systems by using an optimal number of FSRs and IMUs.

1. Introduction

Millions of people suffer from spinal cord injuries, strokes, Parkinson's disease, etc., each year. There are 276 million [1] people who suffer from neuromuscular diseases, making them the second leading cause of death in the world. The joint conditions and neuromotor functions of the patients suffering from neuromuscular diseases change abnormally, which affects their independence, foreboding falls, and quality of life [2]. Strokes typically cause muscles to become spastic at the acute stage, preventing patients from moving freely [3]. A gait cycle evaluates the coordination and balance of muscles in the human body during walking or running. As an example, if the heel strike phase is present in the gait cycle for a longer period, that indicates an abnormality. Researchers have found that stroke patients' gait patterns influence their walking speed [4]. Among post-stroke survivors, moderate walkers would have 21% of normal walking speed without walking assistance, while fast walkers would have 44% of normal walking speed. Gait cycles reflect deviations from usual joint movements, so those changes can be analysed by measuring them [5]. If these attributes are evaluated, the

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therapist might be able to determine whether the gait is abnormal. During the COVID19 pandemic, patients were unable to receive outpatient treatment, so telerehabilitation via web-based tools was investigated [6]. Telerehabilitation can also help the therapist diagnose patients remotely by measuring and recording their gait patterns. Clinical evaluations of abnormal gait patterns qualitatively and quantitatively for neurological patients can help clinicians determine the current health status of these patients and also provide appropriate treatment and rehabilitation plans.

The use of wearable sensors for detecting gait in neurological patients has included IMU, EMG, FSR, accelerometer, magnetometer, and gyroscope [7]. Of these, IMU and FSR sensors appear to be popular and effective [8]. Therefore, this research article is commonly focused on these two sensors. In order to measure the position and orientation of the human foot while walking, IMU sensors can be placed at different locations on the feet [9–13], while in order to assess the kinematics of joints, they can be placed in anatomical locations like the knee or pelvis [14,15]. Nine areas can be identified [16] under the foot based on pressure distribution: Great Toe, Toes, Medial Metatarsal, Middle Metatarsal, Lateral Metatarsals, Medial arch, Middle arch, Lateral arch, and heel. Therefore, FSR sensors can be placed in those locations to cover most of the foot area during the walking pattern of gait cycles (stance and swing phases), such as ten locations [17], seven locations [18], five locations [19] etc covering the heel, toe, metatarsal bone areas under the foot. IMU and FSR sensors may also be used together to develop integrated gait analysis systems [20–22] to monitor both types of data. Despite a large number of studies discussing the use of IMU and FSR sensors for measuring gait cycles, there is still a lack of research regarding the optimal placement of these sensors. Identifying these locations could help researchers develop an effective and efficient gait analysis system with a minimum number of sensors, making it more affordable and wearable for patients.

Additionally, this paper discusses the computational setup for integrating these sensors into local monitoring systems or the cloud. Different types of microcontroller-based platforms such as Ardunio [19], Raspberry Pi 3 [20] are used for interfacing those sensors and transmitting sensor signals through wired [23] and several wireless methods such as Bluetooth [9,18,24,25], Wifi and Zigbee [19,26,27] etc. Nevertheless, the most efficient framework or appropriate sampling frequency for capturing sensory signals is still unclear. This paper provides an overview of the limitations and advantages of several computational frameworks of gait analysis systems, along with their associated attributes, so that the most suitable ones can be selected based on the needs.

This paper is organized into eight sections. In the introduction, the importance, advantages, and limitations of gait analysis systems are explained; in the second section, the stages of gait and its characteristics are analysed; in the third section, gait abnormalities are discussed for different conditions and the relevant sensors are shown for measurement. The fourth section explains how the IMU and FSR sensors are used to measure the gait cycle components; section five discusses the computational platform of gait analysis systems; section six discusses other design parameters, section seven discusses the importance and impacts of the gait analysis systems and finally, section eight concludes the paper.

2. Gait cycle and its attributes

A standard gait cycle involves a repetitive set of steps and strides. An individual's step time can be defined as the time between heel strikes on one leg and the other. It mainly consists of two phases: stance phase and swing phase (Fig. 1). As the foot bears most of the body weight, the stance phase occupies 60% of the gait cycle, while the swing phase occupies 40% when the foot does not touch the ground and the other foot bears most of the weight.

The stance phase and swing phase can be further divided into eight stages [28], which include heel strike, loading response,

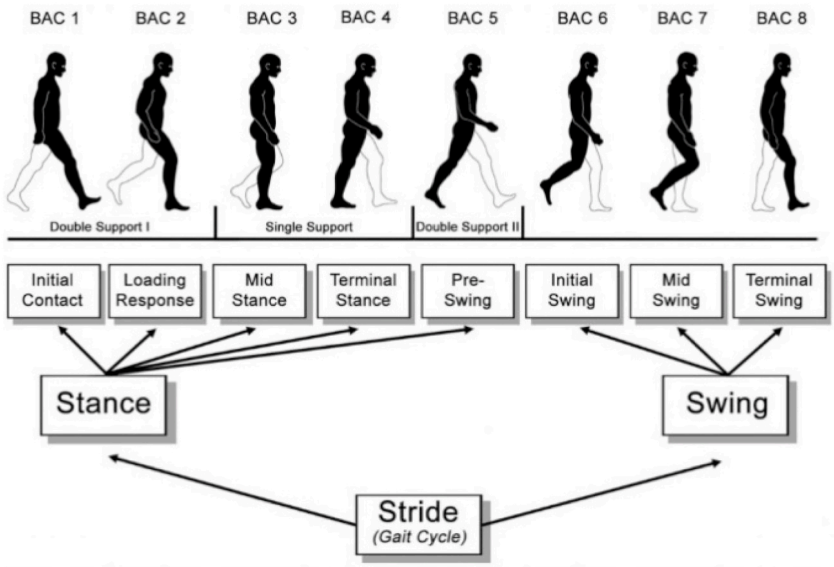

Fig. 1. Stages of the gait cycle [28].

midstance, terminal stance, pre-swing, initial swing, mid swing, late swing. Fig. 1 illustrates each stage in detail. The eight stages of the standard gait cycle are explained here.

Heel Strike: When the foot contacts the ground, exists for a short period.
Loading Response: The foot rolls into pronation as a response to the impact on the ground.
Mid Stance: The moment when the foot stops absorbing the impact and starts to push forward.
Terminal Stance: This stance begins when the heel stops contacting the ground and weight becomes concentrated on the toes.
Pre Swing: The period where the toes stop contacting the ground, also known as toes off stance.
Initial Swing: The ankle goes from flexion to dorsiflexion to let the foot be in a neutral position.
Mid Swing: The advancement of the limb continues.
Late Swing: The ankle gets into a neutral position to prepare to land on the ground again.

The attributes of the gait cycle (Fig. 2) include stride length, stride width, stride angle, step length, step angle, foot rotation direction, foot height, distance covered, time taken, and the pressure points on the foot. The study of locomotion explains the relationship between motion and muscle [29]. The total length of a step is divided between the step length of the left foot and the right foot [27]. The step length of the left foot is measured by calculating the distance from the point of the previous right heel to the new left heel. The same process is followed for calculating the step length of the right foot. The stride length of the left foot is defined as the distance between the left heel and the new heel of the left foot, the same concept applies to the right foot. The step length [30] is twice the stride length. The stride width is determined by the distance between two imaginary centre lines that pass through the heel and second toe of the foot. The step angle is determined by the angle made by the feet from the imaginary centre line, whereas the stride angle is determined by the angle made by the heel during toe-off.

A foot rotation direction can be either an inversion or an eversion [31], where an inversion is when the sole is pointing towards the body's medial direction, while an eversion is when the sole is pointing away from it. A dorsiflexion is an upward movement of the foot, while a plantar flexion is a downward movement. A gait velocity is calculated by the distance covered over a certain time period.

3. Gait abnormalities and measurement sensors

Analysis of a normal gait entails different muscle movements during the gait phases. Innovations in electronics enabled accurate kinematic studies between 1970 and 1980, and mathematical models of the gait cycle were developed. The magnitude of acting forces at the foot, neuromotor function timing, and walking abnormalities can all be evaluated during gait analysis. An analysis of abnormal gait patterns can reveal users' balance during joint movements. The abnormal gait needs to be compared with the normal one to gain a better understanding of it. Additionally, a comparison must be carried out among similar age groups and body types with similar

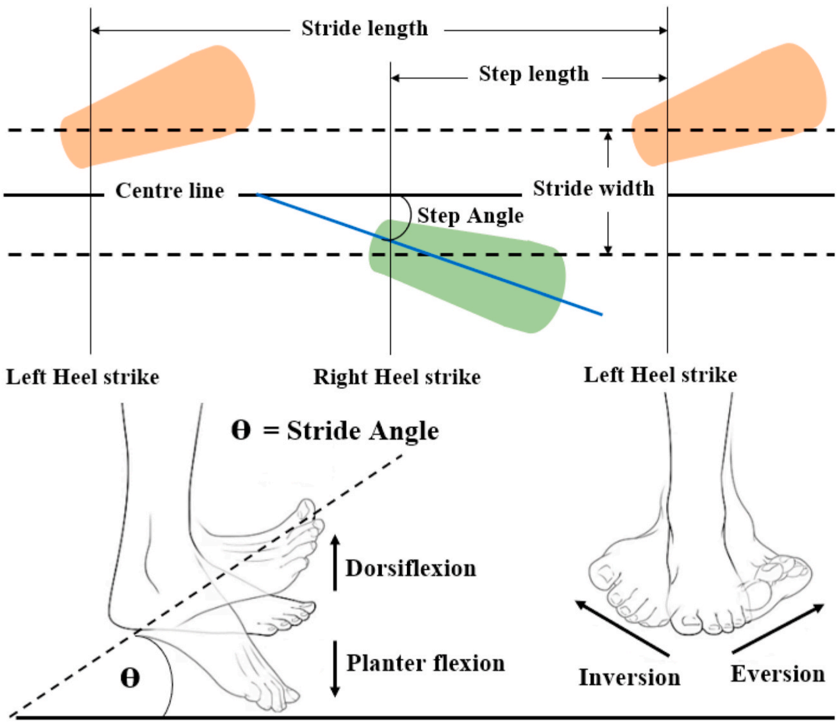

Fig. 2. Attributes of human gait.

anthropometric parameters. All of these gait attributes must be recorded and monitored in order for a therapist to analyse and evaluate the gait performance of an individual.

A study by Li et al. [4], explains how the gait cycle can be affected by stroke symptoms, describing four types of gait patterns: fast walkers, moderate walkers, slow-extended walkers, and slow-flexed walkers. A fast walker can walk at 44% of normal walking speed and does not need assistance. Due to a lack of strength in the plantar flexor muscles, they would lack heel rise in their terminal stance. Compared to fast walkers, moderate walkers have 21% of their normal walking speed. Their plantar flexor muscles are further weakened. A lack of pre-swing forward can also be caused by weakening upper limb muscles such as the gluteus maximus and quadriceps. In general, moderate walkers don't need assistance in walking. The quadriceps muscles of slow-extended walkers are weakened even further. During the swing phase, ankle spasticity occurs. The walking speed of these patients is usually reduced to 11%, and they usually need walking assistance. In their mid-stance, slow-flexed walkers exhibit excessive ankle dorsiflexion. During the swing phase, they usually maintain a leaning posture. The walking speed of these patients is approximately 10% of the normal speed.

It is possible for individuals to experience gait abnormalities due to a variety of conditions. Several factors can cause gait abnormalities [32], including musculoskeletal disorders, neuromuscular and myelopathic disorders, and brain dysfunctions. Individuals with musculoskeletal disorders [33] have a limited range of motion, avoid bearing weight, and have asymmetrical motions. Gait types that fall under this disorder include antalgic gait, coxalgic gait, knee hyperextension gait, etc. In antalgic gait, individuals focus their weight on the unaffected limb to avoid pain. A coxalgic gait involves leaning the upper trunk of the brachial plexus towards the affected leg during the stance phase. It is an unconscious movement that may reduce the force felt by the hip that is affected. In knee hyperextension gait, weakness in the quadriceps leads to hyperextension of the knee during the early stance phase. In order to measure these types of gait abnormalities, IMU [34–36] and FSR [37] sensors are usually used.

In neurological and myelopathic gait disorders [38], the peripheral nerves become paralyzed leading to steppage gait, waddling gait, etc. In steppage gait disorder, partial paralysis of the muscles results in a higher leg lift during the swing phase, so individuals are unable to walk or move on their heels. In waddling gait disorder, weakness in the Gluteus Medius muscle can result in a hip drop on the swinging leg, so patients compensate by tilting the upper trunk in the direction of the leg when they are in stance. In order to measure neuromuscular gait abnormalities, both FSR and IMU sensors are used [21,22,39].

Brain dysfunction can also affect a patient's gait, such as Spastic gait, Ataxic gait, Parkinsonian gait, and frontal gait disorder. Symptoms of spastic gait disorder include the affected limb being stiff and dragging in a semicircular motion due to long-term muscle contractions. In ataxic gait, an uncoordinated walking pattern is caused by dysfunction in the cerebellum. Those with frontal gait disorder suffer from balance issues during movement, have a short step length, and their arm laterally extends and swings less. Those suffering from Parkinson's disease tend to reduce their arm swings and drag their legs. Its progression can lead to a stooped posture, short steps, and slow gait. As the condition progresses, the leg lifts lower than normal, resulting in a shuffling gait. In response to being told to walk faster, individuals tend to take more frequent steps with shorter step lengths. It has been found that both FSR and IMU sensors can be used to analyse gait disorders in Parkinson's disease patients [40,41]. Since IMUs and FSRs are equally useful for evaluating neuromuscular and musculoskeletal disorders, it is necessary to study their working principles, locations, and computational setups.

4. Measurement of the gait cycle

The overall gait cycle can be investigated through two distinguished phases where the stance phase can be divided into two sections, the time when the heel hits the ground and the time when the foot is flat and is in full contact with the ground [28]. The swing phase starts with the toe off the ground, subsequently the knee flexion while making an angle of 60° and ends with initial contact of the heel. Researchers have used several hardware and software tools to measure the gait cycle. The hardware circuit may consist of different types of sensors such as wearable sensors consisting of FSR, accelerometer, gyroscope, and IMU which are usually mounted on the human body for recording joint movement and transformed into gait cycle; motion tracking systems consisting of Kinect [42], Vicon [43] etc. which can also be used for measuring walking pattern and joint movements of user wirelessly. Each type of measurement technique has its pros and cons, for example, a wearable sensor can measure the gait data more accurately than a motion-tracking camera because it is usually either placed on the human body or closed to the particular body segment. On the contrary, wearable sensors can also record unwanted noise signals from the human body and may create uneasiness for users during wearing. The signal is transmitted between the sensor and the local controller via wired or wireless techniques. After investigating a series of wearable sensors used for gait analysis, IMU and FSR sensors are proven to be efficient for measuring gait features. The measurement data from the gait cycle may consist of the walking cycle, the orientation of foot rotation, the elevation of the foot, the distance covered between steps, posture and plantar pressure underfoot. Hence, the working principle of IMU and FSR sensors and their positioning play a major role in measuring the gait data accurately. Other criteria are also considered for the sensor's placement and its construction such as water resistance, temperature compensation, loading effect, energy consumption and battery life. For measuring the pressure at various points underfoot, sensors are usually kept underfoot while placed on the lower limb segments to access the kinematic joint parameters.

4.1. Working principles of sensors

This article is focused on the types, placement and technology of two types of wearable sensors used for gait analysis: FSR and IMU. Foot pressure sensors are made from a piezoelectric, resistive or capacitive material. The working principle of the piezoelectric sensor [44] is based on the applied dynamic pressure. When pressure is applied to piezoelectric material (quartz crystal), an electric charge is built up across the faces. An output voltage can be generated by attaching electrodes across their sides. Although piezoelectric material can be used for low-powered devices and is made of inexpensive elements (quartz or others), there are several disadvantages of piezoelectric sensors such as the amplifiers and other signal conditioners must be carefully designed and positioned very close to the sensor to eliminate any noise interference and errors; some crystals are prone to be water-soluble and could dissolve in a humid environment. Also, the piezoelectric sensor cannot work under static pressure, therefore the output signal eventually drops to zero under constant pressure. Capacitive sensors can also be used for measuring plantar pressure [45]. The working principle of capacitive sensors is based on a similar method of piezoelectric sensors whereas a dielectric layer is used instead of piezoelectric material in the middle and the capacitance is measured across its two layers by attached electrodes [46]. One of the drawbacks of capacitive pressure sensors is their sensitivity to parasitic capacitance which can be removed in several ways explained in the literature provided by Wang et al. [47]. Those sensors should be positioned close to the interface IC. Also, they exhibit non-linearity and temperature dependence.

FSR [26] is made of conductive polymer (Polymer Thick Film) which has the property to change its resistance based on the applied force to its surface. Applied force causes a reduction of resistance in FSR which indirectly increase its conductance. The advantages of using FSR require a simple interfacing circuit compared to other resistive sensors. Its thin size (less than 0.5 mm), low cost (6–11 GBP), and good shock resistance allow it an appropriate material for making foot pressure sensors. On the other hand, FSR has limitations with low precision.

IMU sensor [48] is an electronic measurement device consisting of accelerometers, gyroscopes and sometimes magnetometers. The range of measured parameters includes reaction force, angular velocity and acceleration, and joint orientation. It works by combining the functions of internal components, for example using the accelerometer to detect linear acceleration, and rotational rate using the gyroscope. Some may have a magnetometer as a heading reference. IMU can be used to measure the orientation (Roll, Pitch and Yaw) of the foot [49]. The advantages of the IMU sensor compared to other sensors are reflected in several areas such as its better self-independence and it can estimate the measured value with low cost and optimal power consumption. The disadvantage of IMU triggers accumulated error due to the continuous integration of acceleration with respect to time for calculating velocity and position. It is also slightly more expensive than other sensors. Table 1 shows the allocation of IMU and FSR sensors for measuring several phases of gait cycles.

4.2. *Positioning of sensors*

IMU sensor: It has been found that the placement and orientation of sensors at different locations have a critical impact on the output signal. As the IMU sensor is used for measuring the acceleration, and rotational rate of a specific segment of the human body, those sensors are usually attached around the several points of the foot and legs, not under the foot.

IMU-based gait analysis systems can be used for measuring the usual gait parameters (stride length and duration, stance duration, swing duration and speed) [9], diagnosis [50], evaluating the severity level [10], tracking the progression [51] and continuous relative phase [52] of PD patients. The clinical gait analysis has been evaluated by estimating the foot trajectory [9] and evaluating walking gait patterns in curve line, turning, single task and dual task activities [51] and postural instability or balancing [52] as it is one of the major motor symptoms for the people suffering from PD. Experiments using the IMU-based gait analysis system [9] found that sometimes the stride length of PD patients is shorter compared to healthy persons. There are a few more specific gait patterns that have been founded in PD patients such as support time can be increased up to double [53], reduced step/stride length and gait speed [9], decreased gait symmetry and regularity [11], reduced range of rotation of the hip, knee and ankle [12], disparity of coordination in hip and knee joints during the middle swing phase of the gait cycle [52] etc. IMU sensor-based systems are also used for abnormal gait characteristics in stroke patients by measuring hip-knee cyclograms [34], which would also help to analyse the coordination and kinematics of multiple joints during movement. Experiments with hemiplegic stroke patients show that the hip-knee cyclograms mainly evaluate the adaptability of walking for stroke patients. ML has been introduced to distinguish the gait pattern from healthy users [50]. It has been proved that shank-mounted IMUs are suitable for measuring gait events during straight-line and curved walking for neurological patients, however, cannot detect turning precisely [9].

A low-cost wearable gait measurement system consisting of IMU sensors [24] describes different locations of feet to detect the strides of participants' gait patterns generated from the peak value of accelerometer and gyroscope sensors.

Table 1
Sensors associated with gait attributes.

Attributes	Sensor
Plantar pressure	FSR
Kinematic parameters of foot and leg	IMU sensor
Foot Height	IMU sensor
Foot Orientation	IMU sensor, digital compass
Step Length	IMU sensor, FSR
Gait Velocity	IMU sensor, FSR
Stride length, stride width, stride angle	FSR
Inversion and eversion	IMU sensor
Dorsiflexion, plantar flexion	IMU sensor
Balance	FSR and IMU sensor
Posture	IMU sensor

IMU sensors are usually placed barefoot, a shoe can be avoided due to wear and tear and the possibility of less accurate results. Five locations are chosen to cover several regions of the foot for placing IMU sensors. Those positions are anterior dorsal, posterior dorsal, medial, lateral, anterior dorsal, posterior dorsal and posterior of the foot (Fig. 3). The positions of the sensors are chosen for a specific reason. Location 1 is selected for the medial aspect of the foot because it reduces the movement of the sensor during foot movement, so providing stable sensor data and maximizing the accuracy of the sensor signal from the accelerometer and gyroscopes. Location 2 and 3 are selected for the sensors to be placed at the flexible part of the foot where location 2 is used for evaluating the anterior dorsal aspect of the foot over the second metatarsal pharyngeal joint and location 3 is used for analysing the lateral aspect of the foot over the base of the fifth metatarsal point. Location 4 indicates the mobile part of the foot and can be used for analysing the posterior dorsal over the talar dome anterior whereas location 5 is the most stable part of the foot where the posterior of the foot is evaluated.

IMU sensors can be placed on the shanks [9], hips and knee joints [52], top of the thighs, shanks, feet and pelvis [14,15,34], as shown in Fig. 4. IMUs are attached at both ankles and lower back of the human body for evaluating the static balance in neurological patients [13]. For measuring gait abnormalities in neurological conditions or orthopaedic problems, multi-modal gait analysis is performed by utilizing a combination of IMU and EMG sensors placed on shanks and thighs [54]. A small pilot study with stroke survivors shows that they experienced slightly increased pace and asymmetry during walking outdoors compared to the indoor environment. It is stated that placing the sensor along the same plane on the anatomical segment such as the shank can provide identical signal output.

The step length of users can be estimated by placing an IMU sensor on the front or back of the waist as it is considered as the human body's centre of mass [55]. The estimation method is based on the conditional generative adversarial network (CGAN) model. This placement of IMU is convincing as a practical and easier option to monitor walking activity as it can be kept inside a belt bag. Experiments show an average error of 0.77% for walking on a straight path and 0.88% for rectangular paths. Research also suggests that shank-mounted IMU [56,57] are more robust and can detect gait events more accurately than foot-mounted IMUs [58] because low back or foot-mounted IMUs are less effective in turning motion.

FSR sensor: For measuring the plantar pressure underfoot during walking, it is required to find the pressure distribution area under the foot. It would help to select the location for putting foot pressure sensors in an insole. The pressure under the foot sole can be divided into nine regions [16] such as the great toe, toes, medial metatarsal, middle metatarsal, lateral metatarsals, medial arch, middle arch, lateral arch and heel, as shown in Fig. 5. It also describes the longitudinal arch from the lateral and medial views. The arch of the foot determines an abnormality in gait and running patterns because it would distribute the overall weight of a person over the main pressure points by absorbing and transferring energy while walking or running. The posture of flatfoot can be identified by the medial longitude arch [18]. If the medial longitude arch drops, it will cause a flat foot. As per the anatomical structure of the foot, the location of the navicular bone should be considered for sensor deployment for flat feet.

The usual body pressure can be measured from the main ten anatomical areas [17]. These are the medial and lateral heel area, the medial and lateral midfoot area, the heads of the first, second, and fifth metatarsal area, the great toe, the head of the second metatarsal area, and the lateral metatarsal head area. It has been proved that peak pressure at the heel is usually 2.6 times greater than forefoot pressure. Also, the peak forefoot pressure is located under the second or third metatarsal heads. It is possible to reduce the number of sensor points in a pressure insole by choosing only important pressure points considering specific applications, which ultimately reduces the cost of the system and its complexity [59]. For measuring plantar pressure distribution under the foot during daily living activities, mostly seven locations starting from the heel, great toe, lateral forefoot, centre forefoot, centre midfoot, lateral midfoot, and first metatarsal are used [18]. By integrating the pressure sensors insole, the system becomes wearable, efficient and cost-effective for analysing gait in an individual home rather than going to clinics. Another measurement study [60] of plantar pressure between the foot and shoe shows seven force-sensitive points in each insole namely the centre of the heel, fifth metatarsal, fourth metatarsal, third metatarsal, second metatarsal, first metatarsal, and great toe. After investigating a series of gait analysis systems consisting of foot pressure sensors, thirteen locations have been identified for evaluating plantar pressure underfoot (Fig. 6).

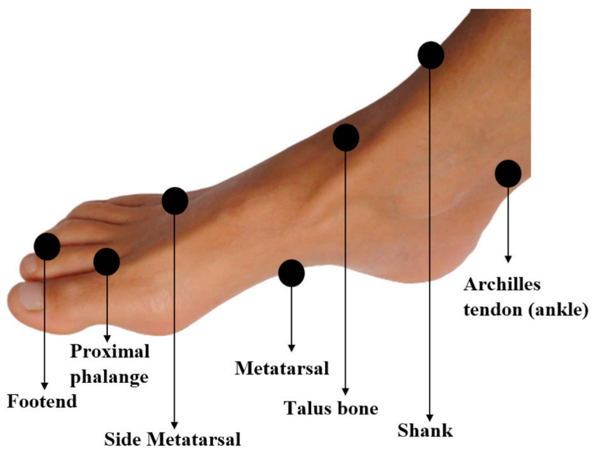

Fig. 3. Placements of IMU sensor.

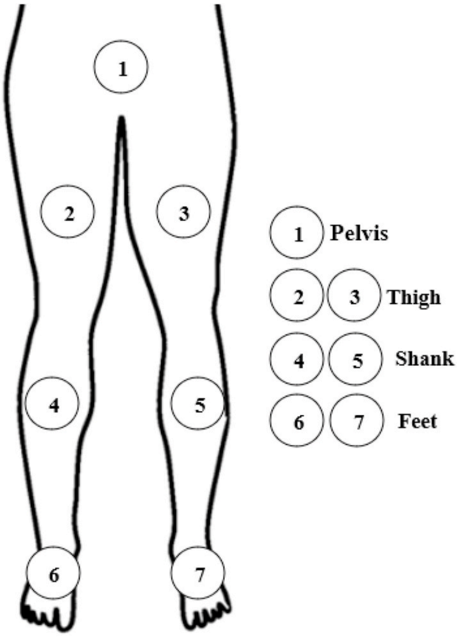

Fig. 4. Placement of IMU sensors.

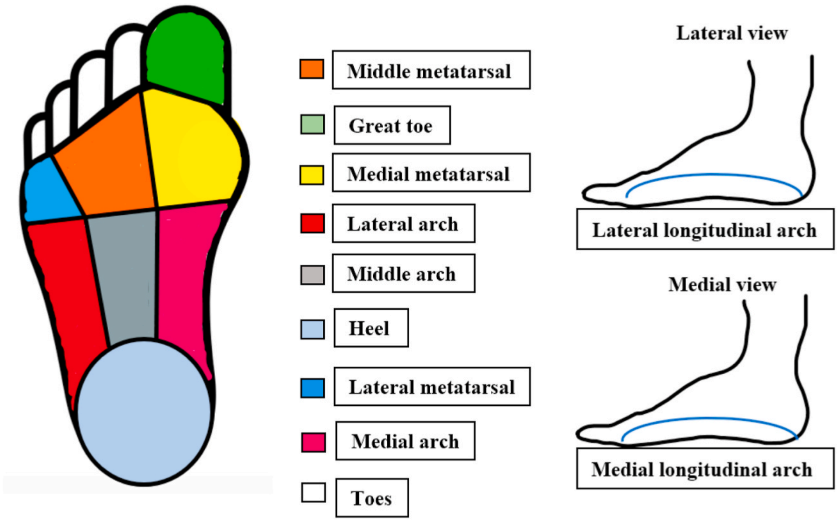

Fig. 5. Regions and arch under the foot.

A few of those FPS gait analysis systems have been described here, most of the systems have used FSR, however, few of those have used piezoresistor and textile sensors. A low-cost and flexible insole system [61] consisting of twelve FSR sensors is used to determine the correlation between ground reaction force and ankle dorsiflexion/plantarflexion movement. For getting a typical plantar pressure distribution, those sensors are attached under the heel, great toe, metatarsal-phalangeal joints, and lateral arch. To be flexible with different foot sizes of users, the system uses longer copper pads in the insole. Four stroke patients have completed 50 steps wearing the flexible insole. Patients have generated lower ankle moments, almost half compared to healthy subjects. Also, the experiment shows that the span of strides is longer for stroke patients compared to healthy subjects. The right locations for FSR sensors can also be selected by a method of the footprint on carbon paper to indicate the strongest pressure points on the foot [19]. For this method, five FSRs are placed at different foot contact points (fore and rear locations), namely the heel, the heads of the first, third and fifth metatarsal bones and the great toe. Those sensors were used to measure the most important stages of the gait cycle such as heel strike, foot flat, heel-off, toe-off and swing phase.

The FSR-based gait analysis system is also used to evaluate gait impairments and tremors due to Parkinson's disease [40,41]. FSR sensors are placed in eight locations (heel, toe, first and fifth Metatarsal, four positions near medial arch) [41] or four locations (great

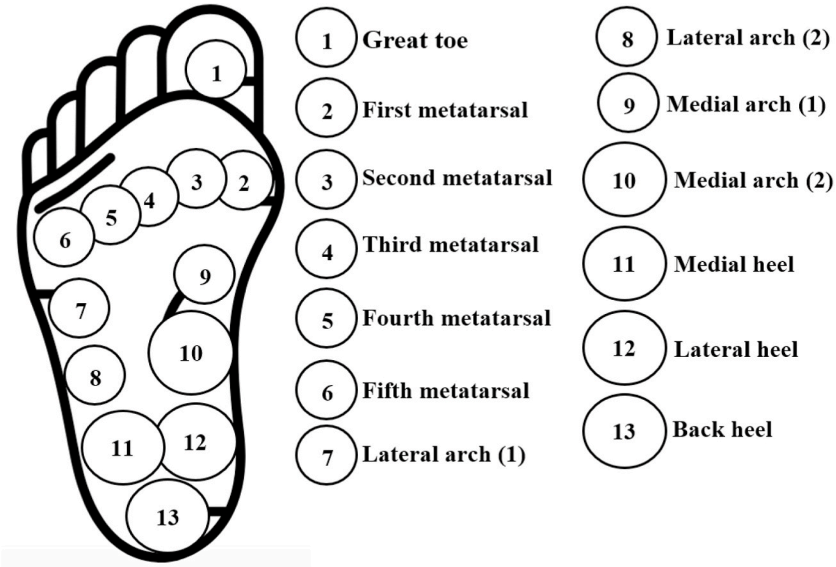

Fig. 6. Layout of FPS positioning.

toe, heel, first and fifth metatarsal) [40] to measure vertical ground reaction force. Mainly the stride time, stance time, swing time and foot strike are used as gait parameters to measure Parkinson's Disease at an average accuracy level of 92.7%.

Another similar type of insole pressure mapping system has been developed by Tee et al. [23] where the system has used FSR as a portable monitoring system for measuring the gait cycle during motion. The sensors are placed at the heel, medial and lateral heel, great toe, first metatarsal and fifth metatarsal to map the pressure distribution of the foot. Experiment with the system shows that FSR 2 (located at the 1st metatarsal) is essential for balancing the body due to its most drastic change of data set among the other sensors. Besides that, the locations of FSR 3 (located at the 5th metatarsal) and FSR 5 (located at the medial heel) have the highest pressure of all while walking. These two locations are also essential to withstand high pressure.

The smart insole developed by Tahor et al. [26] is used FSR to measure vertical ground reaction force. In this design, the difference between the characterization, property and functionality of FSR and flexible piezoelectric sensors is analysed. Sixteen sensors are placed on each insole near the heel, metatarsal heads, hallux and toe. The experiment includes 10 m straight walking six times with the smart insole [26] by twelve healthy subjects. Both types of sensors were calibrated and the results from the FSR-based insole reflect that it can measure vertical ground reaction force reliably and the systems become adaptive to the age, gender, and BMI of the participants. On the other hand, piezoresistive sensors have shown high hysteresis and can only monitor dynamic pressure variation therefore incapable of measuring gait under static pressure.

4.3. Integration of IMU and FSR

Several gait analysis systems integrate IMU and FSR sensors to access the lower joint angles and plantar pressure both at the same time. One such integrated system [20] has used three pairs of nine axes IMU and F-scan system [62] to measure the kinematic and kinetic analysis of a user's gait. The correlation between the plantar pressure data (from the F-scan system) and Kinematic data from IMUs has been found using the Pearson correlation coefficient. Abnormality in gait is also detected by Han et al. [63] consisting of 2 IMUs with 4 FSR where IMUs are placed on the thigh and shank whereas FSR sensors are placed on the heel, first metatarsal, fifth metatarsal, and the hallux. The system measures the shank's angular velocity and acceleration to access different stages of gait cycles and compared them with normal gait by clinicians. Another integrated gait analysis system [27] incorporated both FSR and IMU sensors. In this modular system, an insole with pressure sensors at the big toe, metatarsals first and second, and heel is used for measuring plantar pressure whereas IMU sensors are attached to the user's ankle and foot to determine the directions of Roll, Pitch and Yaw. The developed gait analysis system measures foot height, foot movement, and plantar pressure from sensors. These sensor data from the experiment can be used to calculate stride lengths, step lengths and stance time for analysing the walking cycle. For measuring the spatiotemporal gait of children suffering from NDD and/or ASD, an insole gait analysis system [22] has been designed. This system consists of one nine-DOF IMU and eight FSR sensors located at the hallux, toe, first/third/fifth metatarsals, lateral arch, and medial/lateral calcaneus. Both sensors are placed between two foam layers for protection. After comparing with a gold standard instrument, it has been found that 85% of individuals with ASD show gait abnormalities. Similarly, for measuring the body's progression during the gait cycle through COP trajectory, both IMU and FSR sensors are used [21]. To optimize the number of sensors, the system has used eight FSR and one IMU sensor. It shows larger stride-to-stride variability in the mediolateral COP for patients who experiences higher levels of motor noise due to muscle weakness. To evaluate neuromuscular disorders through spatiotemporal gait, another fully instrumented integrated gait analysis system (consisting of four piezoresistive force sensors, two IMU and one ultrasonic sensor) is developed [22] along with audio-tactile feedback. Two IMU sensors are placed along the midline of the foot, below the tarsometatarsal and proximal shank respectively. Four piezoresistive sensors are placed underneath the calcaneus, the head of the first metatarsal and fifth metatarsal and the distal phalanx of the hallux.

In the process of finding suitable positions for sensor placement, the foot curvature of users also needs to be considered as well. The curvature of the foot can influence the positioning of sensors underneath the foot. A person with flat feet has a different gait cycle from a person with normal feet. An insole-based plantar pressure instrument [18] is designed where five FSR sensors are placed in five locations from the medial to the lateral to evaluate the difference in the plantar pressure between flatfoot and normal foot. The sensors are located around 1 cm distance from the navicular bone of the whole foot. Two types of experiments (static and dynamic) have been carried out with healthy subjects whilst the insole was inserted in the shoes. The static analysis of standing plantar pressure shows that the force measured at the centre of the flatfoot is higher than the normal foot due to pressure across the medial arch. The experiment also supports that the sensors should be placed in the midfoot locations to distinguish between flatfoot and common foot. The dynamic analysis experiment also shows similar results with force differences between flat feet and normal feet. It has been proved that there are significant differences between the medial and lateral arches for flatfoot and normal feet.

5. Computational analysis and system interfacing

This section shows the interfacing circuit of several gait analysis systems between the physical sensor and data acquisition unit (Fig. 7). The interfacing circuit includes the type of microcontroller compatible with the sensor, filter, transmission component (Bluetooth, RF, Zigbee) and several other discrete components such as ESP32, Op-amps, LCD, ADC, SD card etc for amplifying and displaying the signal, transforming analog to digital signal, and storing it. The section also describes the computational method used to depict the raw gait data as technically useful for further analysis, it includes the sampling frequency, noise-removing method, amplification etc.

Most of the existing gait measurement systems have used Bluetooth [9,18,24,25,55] for wirelessly transmitting the data whereas few gait measurement systems developed by Refs. [19,26,27] have used the combination of Bluetooth, Wifi [22] and Radiofrequency [40] for transmitting the data wirelessly. The usual sample frequency for most of the gait analysis systems [9,18,24,25,34,41,55,61,63] is around 100 Hz. There are few other gait analysis systems where the sampling frequency is different; 10 Hz [19], 77 Hz [23], 60 Hz [26], 152 Hz [40], 200 Hz [51], 333 Hz [21], 500 Hz [22] etc. Tee et al. [23] have used the wired data transmission technique between sensors and data acquisition systems to avoid any loss of data. Different types of microcontrollers such as ARM Cortex [22,24], Ardunio UNO [19], PIC18F452 [25], Arduino Micro Pro [18], Arduino Pro Mini [63], Nordic nRF51822 [55] and Raspberry Pi 3 [20] have been used to collect data from the physical sensor and sometimes transfer it to an android device in an IoT platform [24]. To remove the noise and unwanted signals, filters are used, for example in one system [24], accelerometer and gyroscope signals have been passed through Savitzky-Golay (SG) filter to reduce the noise. To avoid the triggering of false stride during the motion for a similar periodicity of walking, gyroscope and gravity sensitivity factors are predicted through a function 'findpeaks' that can distinguish local peaks and ignores small peaks that occur in a neighbouring larger peak. Another IMU sensor-based gait analysis system [9] has used a median filter to reduce the noise from the raw signal. For estimating the gait during curve walking and turning [51], the angular velocity from shank-based IMUs is used to detect the time difference between the initial and final foot contact, after that the data was passed through a high-pass filter to reduce the effect of drift, and then pass through a low-pass filter. The limitation of the IMU is that it accumulates errors through the integration of acceleration into velocity and displacement. A possible solution is the Kalman Filter [64] which can eliminate or minimize errors in the results of IMU sensors. Investigation shows that data from several sensors have been combined to get more accurate data, for example, IMU with EMG [34,54], IMU with ultrasonic [22], accelerometers, gyroscopes, force sensors, bend sensors, pressure sensors, and electric field height sensors [40]. Multisensory fusion data [54,65] have been used to estimate the gait analysis using several machine learning algorithms [41,65]. Gait data from physical sensors are validated by comparing it to other standard methods such as Qualisys motion capture instrument [24], and Motion Analysis [51,61]. In one gait analysis system [26], a CD74HC4067 multiplexer is used to capture a series of sensors as the number of ADC channels in the microcontroller is limited. The power source for these systems is a rechargeable Lithium Battery or power bank.

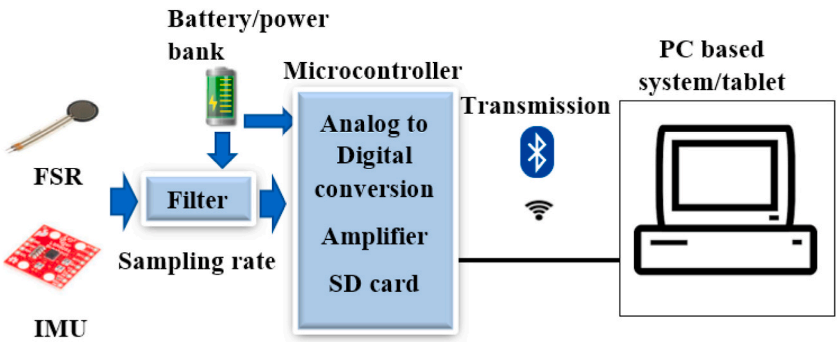

Fig. 7. Interfacing circuit of the gait analysis system.

6. Other design parameters

Besides sensor types, their locations and computational techniques, there are also parameters such as cost, size, weight, temperature effect, loading effect, and functional characteristics such as accuracy, linearity, sensitivity, reproducibility, hysteresis effect that must be considered when designing and developing gait analysis systems. Sensors such as FSRs and IMUs are generally accurate unless they are developed indigenously. In most existing gait analysis systems, healthy participants are tested to evaluate their functional properties. Patients with neuromuscular conditions do not have a typical neuromotor function, their joint movements are affected by stiffness, spasticity, etc., and all these abnormalities will influence their gait cycles. Some questions remain unanswered, however, such as how different foot sizes will be compensated for different ages and genders. There are times when the relationship between force and output signal is not linear, as well as when loading produces a hysteresis effect. The temperature effect (caused by the outside environment and friction between the sensor and the human body) needs to be compensated on the majority of those sensors. Also, in the existing systems, other properties such as the cost and longevity due to prolonged uses have not been discussed [62]. A typical research prototype of a gait analysis system costs between $1000 and $150 [59], and $150 [61], but commercial systems are more expensive like F-scan - $6000 [62] or intellisole - $2000.

7. Discussions

Depending on the individual's health condition, gait cycles and phases differ in length and speed. It is possible for an individual to step slower, the leg can drag on the floor, the leg can rotate outwards before stepping, or the leg can swing too high or too low than normal. All these abnormal joint movements will be reflected in their gait cycle [66]. Patients with different neuromuscular diseases may experience differences in their gait parameters. For example, patients with Parkinson's disease may take a shorter stride [9], while patients with stroke will have a shorter ankle movement [61], and stroke patients will have a longer stride span [61]. A number of research articles [22,33–41,66] on gait analysis have shown that all these abnormalities in gait cycles can be monitored using FSR sensors and IMU sensors, because these sensors are capable of detecting almost all gait characteristics, such as plantar pressure, walking patterns, joint coordination, balance, direction, speed, etc. Currently, gait analysis systems use either FSRs or IMUs, sometimes both, as each has its own strengths and complements the other. A combination of FSR and IMU sensors [20–22,27,62,63] has proven to collect more data than either sensor alone. As an example, the system reported in Ref. [63] combines FSR and IMU sensors together in order to capture the stance and swing phases of gait analysis. A sensor's position is crucial to the user's comfort during exercise, data accuracy, and performance monitoring. In order to evaluate a user's clinical attributes, sensors must be placed at specific anatomical points. Based on the results of the survey, seven FSR sensors can be considered as a standard to be placed under seven important points, such as the big toe, heel, first, third, and fifth metatarsals, and sometimes two sensors near the medial arch for flat feet. It can be considered that IMU sensors should be placed on feet, shank, thigh and Pelvis for accessing the kinetic and kinematic parameters of gait data. The standard sampling frequency of sensor data is usually kept at 100 Hz. Microcontroller kits such as Arduino, PIC, and ARM cortex have been used for collecting raw sensor data. Using Bluetooth or WiFi, sensors can be connected to a PC-based system and data can be transmitted wirelessly. This would enable virtual live monitoring by healthcare workers and enable the remote display of results. As Bluetooth transmission requires low energy, it can optimize energy consumption for long periods of time, making it ideal as a wireless transmission medium.

Using IMU and FSR sensor-based gait analysis systems, the development of a body-based wearable IoT sensor network has the potential to be used for a variety of applications, including fall detection in the elderly, assistive robotics, prosthetics and orthotics, clinical rehabilitation, and telerehabilitation. It can, for instance, support the well-being of elderly people who live at home or in care facilities by detecting or predicting any falls [67]. Hence continuous monitoring of vulnerable elderly people by measuring their gait can be a great benefit and an integral part of smart home features [68]. A patient with neurological disorders may need active joint support, such as an exoskeleton, to support the joint movement, so gait data can be used to adjust the parameters of the exoskeleton [69]. The gait data will not only indicate the initiation of joint movement, but also any abnormal activities that can be supported by the appropriate joint movement before an accident occurs. Similarly, it can be used for controlling the parameters of active prosthetic and orthopaedics devices [70]. As a result, the features of human gait could help clinicians provide appropriate and relevant rehabilitation therapy [71] to patients suffering from neurological disorders [38], and post-surgical complications [72]. With the use of gait analysis systems, it is possible to identify the deformities of specific joints and muscles, in order to develop joint-specific exercises for recovery. Furthermore, gait characteristics are used not only to assess a patient's current health status but also to determine their recovery process [73].

During the COVID pandemic, in many hospitals, face-to-face rehabilitation services were postponed for an extended period to reduce the spread of the virus [74]. When services resumed, many patients or their caregivers refused to attend face-to-face clinics for fear of contracting the virus. Consequently, the rehabilitation service was experiencing a significant backlog of patients. Several patients missed assessments for spasticity, resulting in unnecessary deterioration. In order to make these interventions remotely, quantitative and qualitative evidence of the patient's movement was needed. Thus, using the sensors for monitoring and recording the performances during rehabilitation exercises promotes the remote assessment and provision of rehabilitation exercises and posture management for the patients [75]. Despite the backlog of patient rehabilitation services caused by the pandemic, the usual traffic of rehabilitation services at hospitals is still too high. For example, an analysis of NHS UK data found that over 10,000 people have been waiting more than a year for neurological rehabilitation services [76]. Rehabilitation costs [77] place a financial burden on health services, for instance, the total annual societal costs of supporting stroke patients worldwide amount to £26 billion each year, including £8.6 billion for the NHS UK and social care [77]. Measuring gait parameters using wearable sensors could thus provide a sustainable solution for telerehabilitation in the future. Having these types of technologies will allow patients to continue rehab at home without travelling to a rehabilitation facility, resulting in a reduction in the hospital's carbon footprint.

8. Conclusions

This review paper discusses the optimal locations for placing IMU and FSR sensors on the human body and its standard monitoring setup for accessing gait abnormalities, thereby reducing the number of wearable sensors for developing an efficient gait analysis system. Eventually, this approach will provide researchers with an efficient and affordable method for developing gait monitoring systems and exploring a range of abnormalities in their patterns which cause different neurological disorders. Hence clinical gait data can be used to evaluate the health conditions of patients for diagnosis and treatment purposes, to monitor their conditions for the recovery process and to use those data for prognosis purposes. This research article also explores the diverse applications of gait abnormalities in telehealth and robotics. Detailed discussions highlight how gait analysis can be used in rehabilitation, wearable devices and IoT applications. Advancement of digital technology, IoT and wearables develop opportunities for remote medical care. This would help to provide more customised, personalised, efficient and cost-effective care services. Most of all, it will push care services out of hospitals. Minimal contact with the human body based on a reduced number of sensors and optimum components in their computational setup would enhance patients' experience in the monitoring process, improve device use and provides real-world information with effective management of resources. The collection of user-centric clinical gait data from patients is also used for developing futuristic smart and artificial intelligence tools. Therefore, IMU and FSR sensors' data are not only used for smart monitoring and guiding tools but also for predicting their recovery. This paper is limited to the technical details and configuration of IMU and FSR sensors, however, there are other types of sensors used for gait measurements such as motion tracking sensors, EMG sensors etc. It is also important to explore those sensors in order to get an overall picture of gait measurement systems.

Author contribution statement

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No data was used for the research described in the article.

Declaration of interest's statement

The authors declare no conflict of interest.

Nomenclatures

IMU	Inertial Measurement Unit
IoT	Internet of Things
FPS	Foot Pressure Sensor
RF	Radiofrequency
FSR	Foot Sensitive Resistor
LCD	Liquid Crystal display
PD	Parkinson's disease
NDD	Neurodevelopmental disorders
EMG	Electromyogram
ASD	Autism spectrum disorders
ADC	Analog to Digital convertor
SG	Savitzky-Golay
BMI	Body Mass Index
COP	Centre of Pressure
DOF	Degree of Freedom
NHS	National Health Services

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